Job Creation in Tight and Slack Labor Markets

Lukas Buchheim (LMU Munich)
Martin Watzinger (LMU Munich)
Matthias Wilhelm (LMU Munich)

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Ludwig-Maximilians-Universität München | Humboldt-Universität zu Berlin
Spokesperson: Prof. Dr. Klaus M. Schmidt, University of Munich, 80539 Munich, Germany
+49 (89) 2180 3405 | info@rationality-and-competition.de

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Lukas Buchheim Martin Watzinger Matthias Wilhelm*

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Abstract

Do investment programs create more jobs in tight or in slack labor markets? We study this question using data from a large, long-term photovoltaic invest scheme in Germany. Comparing counties with high and low unemployment both over time and across space, we find that photovoltaic installations created at least twice as many jobs in slack than in tight labor markets. Our results suggest that the differences in job-creation are not driven by changes in the composition or prices of investment, capital-labor substitution, or regional migration. This leaves crowding-out as the most plausible mechanism.

Keywords: Local Employment Multiplier, State-dependent Multiplier
JEL Classification: E24, E62, J23, R23

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*Department of Economics, LMU Munich. Corresponding author: Martin Watzinger, Akademiestrasse 1, 80799 Munich, Germany, martin.watzinger@econ.lmu.de. For helpful comments and suggestions we thank Daron Acemoglu, Gabriel Chodorow-Reich, Simon Jaeger, Markus Nagler, Monika Schnitzer, Andreas Steinmayr, Uwe Sunde, and seminar participants at various conferences and seminars. Lukas Buchheim and Martin Watzinger gratefully acknowledge financial support from the DFG through CRC TR 190. Matthias Wilhelm gratefully acknowledges financial support from the Elite Network of Bavaria through the doctoral program Evidence-Based Economics. Parts of this paper were written while Martin Watzinger was visiting Boston University and Matthias Wilhelm was visiting MIT; we thank both universities for their hospitality.

1 Introduction

In 2000, Germany implemented a generous subsidy scheme for investments in renewable energy. The scheme mandated grid operators to purchase electricity from renewable sources at above-market prices. The result of this subsidy were unprecedented investments in photovoltaic systems. Between 2000 and 2012, 1.26 million rooftop photovoltaic (PV) systems were installed, corresponding to investments of €64 billion. Yearly investment peaked at 0.6% of GDP in 2010 and resulted in an increase of the share of solar energy in total German electricity consumption from zero to 4.2% between 2000 and 2012.[1]

In this paper, we study this program to shed light on an important question in empirical macroeconomics: Does investment create more jobs in slack than in tight labor markets? A state dependent labor market response to additional demand is one main channel of how the government spending multiplier may differ across different states of the economy.[2] However, despite an extensive debate, the results regarding state dependent multipliers are so far inconclusive. Using time-series methods, some recent studies find a strong state-dependence of multipliers (e.g., Auerbach and Gorodnichenko, 2012, 2013; Bachmann and Sims, 2012; Fazzari et al., 2014), while others find differences in the multiplier only for a subset of specifications, depending on the data and methods used (e.g., Owyang et al., 2013; Caggiano et al., 2015; Biolsi, 2017; Ramey and Zubairy, 2018).

A key challenge for assessing whether employment responses to investment are state-dependent is to find comparable demand shifts in all states of the economy. This is difficult for three reasons: First, the *volume* of (public) investments may be a function of the state of the economy. For example, the size of a stimulus program in a recession might depend on the severity of the downturn. Second, the *composition* of investments may also be state dependent. During recessions, stimulus programs might be designed in a way that allows for quick implementation. In contrast, public investment in booms is often targeted at major projects with long planning horizons designed to increase the long-run growth potential. These different types of investment may have different employment and output effects due to their nature and not due to differences in economic circumstances.[3] A third reason is, as pointed out by Gorodnichenko (2014) and Ramey and Zubairy (2018), that identifying state-

[1] https://ag-energiebilanzen.de/index.php?article_id=29&fileName=20171221_brd_stromerzeugung1990-2017.pdf, last accessed on September 1st 2017.

[2] The other main channel for a state-dependent multiplier in the literature is unresponsive monetary policy. In our setting, the interest rate does not increase with additional demand, thus preventing crowding-out of investments.

[3] Furthermore, the effects of investment in recessions may be comparably easy to detect empirically due to their quick implementation. In contrast, investment with a focus on long-run growth may be much harder to detect, both in the short and in the long run.

dependent effects of demand shocks is econometrically challenging, as one needs *sufficient variation* in these shocks *for each of the different states* of the economy.

In this paper, we exploit investments in rooftop photovoltaic systems in Germany to address these challenges. First, both over time and across all 400 German counties, investment was driven by factors that are plausibly orthogonal to employment dynamics. Over time, investment were largely determined by the world price of solar panels relative to the amount of the subsidy. The spatial variation in investments was primarily driven by the amount of local solar radiation and the availability of suitable rooftops.[4] Second, we directly observe the physical amount of investments, so that neither composition nor price changes of investments can affect our results. In addition, the technology of installing PV systems has remained unchanged. Hence, each PV installation of a given size constitutes the same demand shock regardless of its vintage and location. Third, since at least 2004, installing rooftop PV systems became profitable in all German regions, causing a steady stream of investments. There is ample identifying variation in these investments for any plausible partition of German counties into groups with slack and tight labor markets due to the substantial variation in the factors that drive the profitability of investment.

In our main analyses, we find that the installation of PV systems created significantly more jobs in slack labor markets characterized by high unemployment than in tight labor markets with low unemployment. At times when a county is above its own long-run average unemployment rate, the installation of PV systems with power output capacity of one megawatt peak (MWp) led to 37 new jobs on average. In contrast, the same additional demand only created a net increase of 3 jobs when unemployment is below the county average. This difference is statistically significant and translates to 1.17 jobs per investments of €100,000 in slack years relative to 0.1 jobs in years with tight labor markets. We find essentially the same result if we compare the effect of investments on employment in the cross section, that is, in counties with high or low unemployment relative to their state average in a given year. These results are robust to various other ways of defining slack and tight labor markets, and remain qualitatively unchanged when we instrument PV installations with their profitability as measured by the investments' net present value.

There are several potential explanations for the higher number of jobs created in slack than in tight local labor markets. For example, in search and matching models, tighter labor markets can lead to crowding out (Michaillat, 2014).[5] Additional demand for PV

[4] On top of that, we use high-dimensional time fixed effects in our empirical strategy to filter out potentially correlated employment trends.

[5] Specifically, in Michaillat (2014) the higher crowding out occurs due to the convexity of the quasi-labor supply function. Roulleau-Pasdeloup (2017) suggests a similar mechanism for how the difference in the fiscal multiplier may differ with respect to labor market tightness in the presence of search frictions and when

installations might draw workers from other jobs in tight labor markets, and create new jobs only in slack labor markets. Another channel could be that in a tight labor market, companies might substitute labor for capital, e.g., by using a machine instead of labor for moving solar panels to roofs. A third explanation is that in slack labor markets, additional demand in a county is accommodated by an increase in employment in the same county, while in tight labor markets additional demand leads to an increase in employment mainly in other regions.

To provide evidence on the mechanism, we estimate the employment gains across sectors and from additional demand in nearby regions. The evidence from these exercises favors the crowding-out mechanism put forward by Michaillat (2014). The differential employment gains seem to be caused by a general effect of labor market tightness on employment creation. We find that the difference in new jobs across economic circumstances is driven by differential employment gains in both high-exposure sectors—the sectors which include those types of firms that typically install solar panels—and sectors that offer local, non-tradable services. This suggests that the differential employment gains cannot be explained by differential capital-labor substitution alone. In addition, a county's employment is largely unaffected by additional demand in surrounding regions, irrespective of the state of the county's labor market.[6] This speaks against differential labor demand spillovers across regions as an explanation for our findings.

This paper provides comprehensive evidence from panel data that the employment response to demand shocks depends on the state of the labor market. There is an increasing number of time series studies that focus on estimating the public spending multiplier conditional on the state of the economy (see the works cited above). In contrast, the literature estimating the so-called local (employment) multiplier is thus far primarily concerned with assessing unconditional effects (see Fuchs-Schündeln and Hassan, 2016 and Chodorow-Reich, forthcoming, for recent reviews). Nevertheless, some papers from this literature provide estimates of the local multiplier conditional on different measures of local economic slack. Nakamura and Steinsson (2014) are closest to our work in two ways. They also consider a relatively narrow spending measure—military procurement contracts—and also split their

wages are downward rigid. Recent work by Rendahl (2016) also emphasizes the role of the labor market for generating differential effects of fiscal spending in booms and recessions, albeit with a different channel. Here, at the zero lower bound, changes in government spending generate persistent changes in employment, thereby increasing expected future demand, and, by extension, future income and employment. This mechanism crucially relies on differential expectations regarding the path of the entire economy at and away from the zero lower bound. For most of our sample these differential expectations are not present and, hence, cannot explain the results; this holds in particular when we condition on cross-sectional differences in labor market tightness at the same point in time.

[6]This finding is plausible, as it is usually small and local firms like electricians, architects, or heating contractors that install PV systems.

sample according to the level of unemployment. Unlike this paper, however, they only find small and statistically insignificant differences in employment gains due to military spending shocks, but sizable differential effects on output. Yet, it remains unclear to which extent these differences are driven by different labor market conditions or varying composition of military demand. In their own words, "military purchases [comprise] of everything from repairs of military facilities to the purchase of aircraft carriers" and these differences in composition may be correlated with labor market conditions. All other studies consider even more aggregate measures of demand shocks, mostly shifts in total government expenditures (Cohen et al., 2011; Brückner and Tuladhar, 2014; Dube et al., 2014; Suárez Serrato and Wingender, 2016; Shoag, 2015; Adelino et al., 2017). Among these papers, Shoag (2015) stands out for showing that slack in the labor market leads to higher output and employment gains of public spending both when considering cross-sectional and time series splits of the data, similar to our findings. Furthermore, Cohen et al. (2011) are the only ones to find negative effects of government spending on firm-level outcomes overall, but less so in states with slack labor markets. That being said, none of these papers attempts to identify the mechanism of why slack labor markets lead to higher employment gains of demand shocks, as we do here.

While this is the first paper to estimate employment effects of PV installations, the recent increase in the adoption of solar energy has served as a case study to answer other questions of wider economic interest. De Groote and Verboven (2016) use data on solar energy adoption and subsidies from a program in the Netherlands to identify the optimal subsidy design to foster private investments. Pless and van Benthem (2017) exploit similar data from California to study the pass-through of such subsidies to buyers and renters of solar panels. Lastly, Comin and Rode (2013) ask whether investment in solar energy causes individuals to vote for (green) parties that promote the adoption of renewable energy.

The remainder of this paper is structured as follows. Section 2 describes the institutional background of the Renewable Energy Act and the data. We lay out the empirical approach in Section 3, where we also discuss the identifying variation in PV installations. Section 4 reports the main results. Section 5 discusses potential mechanisms and Section 6 concludes.

2 Institutional Background and Data

The German Renewable Energy Act (*Gesetz für den Vorrang Erneuerbarer Energien*) went into effect on April 1st 2000 with the aim to increase the share of renewable energy (photovoltaics, wind, biomass, hydropower, geothermal) in German energy production. The current target is that 80% of German electricity consumption stems from renewable energy sources by 2050. In order to achieve this, the law rests on two key mechanisms: First, the law mandates grid operators to connect all (household) renewable energy systems to the grid and to purchase the produced electricity. Second, this electricity is remunerated with a feed-in tariff above the market price. The relevant feed-in-tariff for a given source of renewable energy is determined at the time at which it is connected to the grid and remains fixed for 20 years thereafter; that is, for an existing renewable power plant (e.g., a PV system), the feed-in tariff cannot be changed retroactively. The feed-in tariff itself is financed via a surcharge on electricity consumption for all consumers. Overall, the law generated a favorable investment environment for renewables, leading to an increase in the share of renewable energy in total energy production from 7% in 2000 to 23% in 2012.[7]

2.1 Physical Investments in Rooftop PV Systems

An additional key provision of the Renewable Energy Act is that until July 2014 it mandated grid operators to collect and publish detailed data on all renewable energy power plants. The data provided by the grid operators has been aggregated, cleaned, and validated by the *Deutsche Gesellschaft für Sonnenenergie* (DGS), which is the German branch of the International Solar Energy Society.[8] We use the data of the DGS up to and including 2012 because data postings have become more sketchy in 2013 ahead of the change in the data publishing requirements and because the number of new installations has stalled in 2013/2014, when the 2012 amendment of the Renewable Energy Act drastically reduced the feed-in tariff.

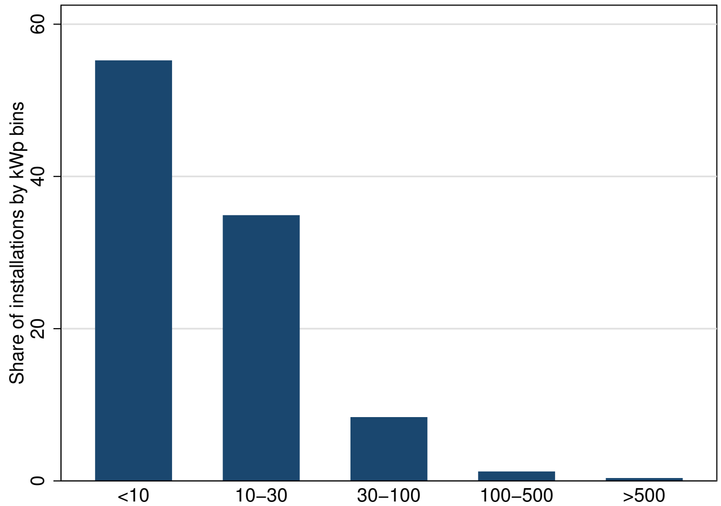
Every entry in the DGS database contains the type of the renewable energy power plant (photovoltaics, biomass, wind, hydropower, geothermal), the exact street address, the date of commissioning, and the power output capacity. The date of commissioning determines the applicable feed-in tariff (which, thereafter, is fixed for 20 years). For this reason, plant operators usually commission each system as soon as it is connected to the grid, as the feed-in tariff has in general been falling over time. We can thus exactly pinpoint when a PV system was constructed. The power output capacity, in turn, is a measure of the size and, hence, the physical investment volume of a PV system. For PV systems, output capacity is measured by its peak energy production under ideal working conditions, denominated either in kilowatt peak (kWp) or megawatt peak (MWp, with 1 MWp equal to 1,000 kWp).

There are two types of PV systems: rooftop systems and systems mounted on the ground (so called greenfield systems). Our analyses focus on the installation of rooftop PV systems.

[7]Note that this includes all types of renewable energy sources, not just photovoltaics.

[8]The raw data from the DGS are available at: http://www.energymap.info/download.html [last accessed on March 12th 2018]. From July 2014 onwards, the data are published, in a different format, by the *Bundesnetzagentur*, a federal agency.

Figure 1: Distribution of the Power Output of the PV Systems Installed



Note: The figure shows the percentages of PV systems installed between 2000 and 2012 by five bins of potential power output as measured in kilowatt peak (kWp). The highest category of more than 500 kWp contains 4,395 projects with a total of 9,000 MWp. The remaining categories contain 1.28 million projects with 20,792 MWp.

As the information regarding the type of the PV system is missing in a subset of the data, we restrict attention to PV systems with an output capacity of less than 500 kWp.[9] As shown in Figure 1, fewer than 1% of PV systems installed between 2000 and 2012 have a capacity greater than 500 kWp. We also exclude those data entries from the analysis that the DGS has deemed to have errors, such as wrong addresses.

From these raw data entries, we construct yearly physical investment in rooftop PV systems at the county level as the sum of installed capacity within a county in a given year. The main advantage of measuring physical investments, as opposed to monetary investments, is that physical investments capture real labor demand irrespective of variation in the prices of the production factors over time or across space. This is particularly relevant here, given that the price of solar panels, the main capital input, varies considerably over time and given that the relevant wages may vary across space conditional on the state of the local labor market.

2.2 Determinants of Rooftop PV Installations

The volume of PV installations over time and across space is determined by five main factors: total costs, the feed-in tariff, the prevailing interest rate, solar radiation, and rooftop space.

[9] A rule-of-thumb is that 1 kWp of power output capacity requires around 8-10 m^2 of space, implying that 500 kWp require around 4,000 to 5,000 m^2 (43,056 to 53,820 square feet) of rooftop space. The majority of roofs are smaller.

Total costs are obtained from an industry survey (Bundesverband Solarwirtschaft e.V., 2012) that asks a representative sample of 100 companies about their total installation price per kWp. The resulting cost data are available quarterly since 2006. Prior to 2006, we use the yearly data from Janzing (2010). According to this data, the average installation costs of PV systems in our sample amount to €3,121 per kWp. We use this figure to calculate the costs of job creation based on the estimated employment effects of physical PV installations.

The second investment determinant is the feed-in tariff for electricity from photovoltaics specified by the Renewable Energy Act. The feed-in tariff typically varies by year; when there are multiple changes during a year (as in 2009 and 2012), we take the yearly average.[10]

The revenue flow from selling solar electricity at the price of the feed-in tariff accrues over time. The net present value of these revenues are calculated by discounting the expected payments using the "average interest rates for mortgage loans" prior to 2003 and the "effective interest rates of commercial banks for housing loans" after and including 2003, published by the Bundesbank.

The profitability of PV systems is driven by their energy production, which is a function of the amount of solar radiation and the available rooftop space. Data on solar radiation is taken from the Photovoltaic Geographical Information System (PVGIS) of the European Union (Huld et al., 2012). From the grid cell GIS data on the "yearly average global irradiance on the optimally inclined surface," we calculate the average radiation (measured in kWh per square meter) at the county level.

For estimating the rooftop potential for solar energy production (in kWp), we follow the methodology of Lödl et al. (2010), who provide a detailed estimate of rooftop potential for the state of Bavaria. Lödl et al. first classify municipalities into four categories ("very rural," "rural," "suburban," and "urban") based on five observable municipality characteristics: population, population density, settlement area, average living area per capita, and the number of apartments per building. Second, they use aerial maps of 4,500 dwellings to estimate the average rooftop potential conditional on the settlement area and the municipality's type. We apply their classification of municipalities to Germany and compute each municipality's rooftop potential using the conditional estimates from Lödl et al. (2010). Rooftop potential at the county level is given by the aggregate of these municipality-level estimates. Appendix A.2 provides a detailed description of the calculations.[11]

[10] The capacity bins that determine the exact feed-in tariff for each PV system have been changed in April 2012. Between April and December 2012, we use the feed-in tariff applicable to PV systems with a capacity of less than 10 kWp. Prior to April 2012, we use the feed-in tariff applicable to systems with less than 30 kWp capacity.

[11] A preferable approach would be to use building-level estimates of rooftop potential like Google's project "Sunroof." Google sunroof has been rolled out in Germany in May 2017, but only includes data for major municipalities thus far (https://www.eon-solar.de/, last accessed on March 12th 2018).

2.3 Employment Data and Control Variables

The data on employment and unemployment is from the Federal Employment Agency, which collects this administrative data to determine social security contributions and eligibility. The data is of single-digit precision and has minimal sampling error. The employment data counts every employed individual who lives in a county and pays social security contributions, including part-time workers but excluding the self-employed and public servants. In our main analyses, we use the yearly mean of the quarterly available employment data measured on the last day of the quarter.

From the Federal Employment Agency we also obtained industry-specific employment data on the three-digit industry level. This data is measured at the end of the second quarter of every year.[12]

The control variables are either from the Federal Employment Agency or the Federal Statistical Office, unless noted otherwise. The data on county types ("non-city" or "city," where "city" is a county consisting of a single municipality, a so called *Kreisfreie Stadt*), a dimension of the time fixed effects we employ, and on spatial planning regions (*Raumordnungsregionen*), the level of clustering, are from the Federal Office for Building and Regional Planning.

In the empirical analyses, all variables are measured yearly at the county level and normalized by a county's working-age population (between 15 and 65 years of age) in 2003 unless noted otherwise. This normalization facilitates the comparison of variables across counties. Appendix A provides further details regarding the data.

3 Empirical Model

The goal of our empirical strategy is to assess whether the effect of physical investments in rooftop PV systems on employment differs conditional on the state of the labor market. We identify the effect of investment in PV systems on employment by exploiting variation in installations within German counties from 2003 to 2012 using the following model

$$\begin{aligned}Employment\,p.c._{c,t} &= \beta\, PV\ Installations\, p.c._{c,t} + CountyFE_c \\ &\quad + \delta_{c,t}\,\mathbb{1}[Year_t \times State_c \times CountyType_c] + Controls_{c,t} + \varepsilon_{c,t}, \quad (1)\end{aligned}$$

[12] In 2008, the German industry classification was revised (corresponding to NACE Rev. 2). We cross-walk the data post 2008 to the industry classification of 2003 (*WZ 2003*) using the official correspondence table provided by the Federal Employment Agency.

where the index c denotes the county, t denotes the year, and "p.c." (for "per capita") in the variable name indicates that the variable is normalized by the county's working-age population measured in 2003. PV installations are measured in megawatt peak (MWp).

We control for county fixed effects and year fixed effects for each county type and state combination (given by $\delta_{c,t}\,\mathbb{1}[Year_t \times State_c \times CountyType_c]$).[13] To adjust for labor market dynamics due to population flows, we control for population growth via the ratio of the working-age population in year t and the working-age population in 2003. We also account for construction activity as measured by the number of buildings completed in year t. Construction activity is likely to both affect the demand for rooftop PV installations and employment. We show in Appendix C that our results are unchanged for different sets of covariates. The standard errors are clustered at the level of 94 German spatial planning regions (*Raumordnungsregionen*) to account for potential geographic and serial correlation within these regions.

Investment in photovoltaics is mainly driven by profitability considerations. The determinants of profitability of PV systems themselves are either predetermined or unaffected by regional characteristics and observeable. This allows us to use OLS for our main specification and to construct an instrumental variable for investment. Section 3.1 describes the identifying variation in PV installations across time and space and the construction of our instrumental variable.

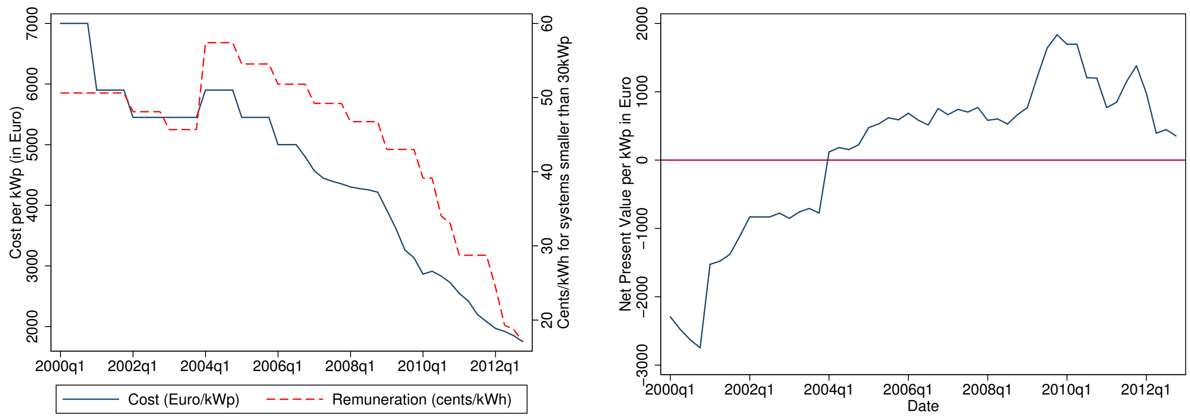
To investigate whether the employment effect of PV installations depends on the state of the economy, we need to define whether or not a labor market is "slack" or "tight." We follow the literature in this respect and define labor market slackness of a county according to how the past performance of the labor market compares to a benchmark. We then split our sample by slack and test whether the effects differ with respect to the state of the local labor market. Section 3.2 explains in detail how we classify labor markets as "slack" and "tight."

3.1 Identifying Variation

The profitability of a rooftop PV system is determined by how much electricity can be produced, how high this electricity is remunerated and by the costs of installing and maintaining the system. The remuneration and costs exhibit substantial variation over time, but none across space, whereas the reverse is true for the potential for electricity production.

[13] Counties are defined according to their boundaries in 2012, resulting in a total of 402 counties. We omit Hamburg and Berlin, as these are city-states and their employment outcomes are fully captured by the year fixed effects at the state level.

Figure 2: Feed-in Tariff, Installation Costs, and Net Present Value of PV Systems



(a) Feed-In Tariff and Installation Costs

(b) Net Present Value

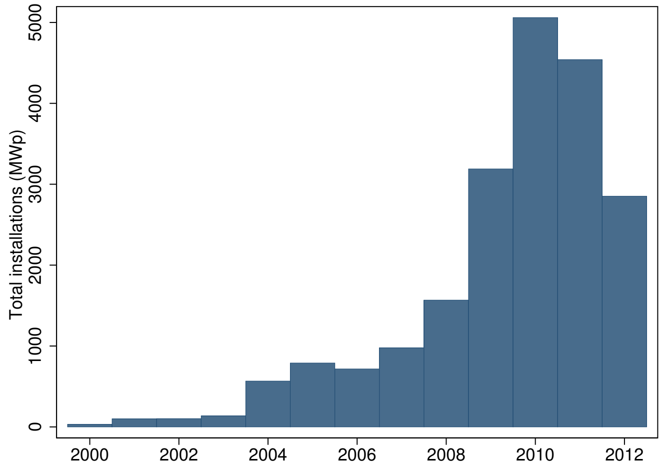
Note: Panel (a) shows the average costs (in Euro) per kWp for PV systems smaller than 100 kWp (solid line, left axis) as well as the feed-in tariff (fixed for 20 years, in Euro-Cents) per kWh of energy produced by a PV system smaller than 30 kWp conditional on when the system is connected to the grid (dashed line, right axis). Panel (b) displays the net present value (NPV) per kWp for a PV system with less than 30 kWp of capacity given the costs and the feed-in tariff from Panel (a). See the text for details.

Determinants of Investment over Time The feed-in tariff is one of the time-varying determinants of the profitability of a rooftop PV-system. The dashed line in Panel (a) of Figure 2 shows the feed-in tariff per kWh in Euro-Cents (right axis) of produced electricity for rooftop PV systems with less than 30 kWp, conditional on the date the system was connected to the grid. The initial feed-in tariff was 50.62 Cents in 2000, and scheduled to decrease by 5% each year from 2002 onwards. However, reflecting the policy goal of the government at the time to boost renewable energies, the feed-in tariff was raised to 57.40 Cents in 2004, with yearly degressions of 5% in 2005 and of 6.5% thereafter. The ensuing boom of solar energy production led to a steep increase in the cost of the policy. Further amendments of the law in 2009 and 2012 aimed to keep these costs in check, prescribing steeper degressions conditional on the volume of new installations in the previous year.

Falling costs of PV systems have also contributed to making PV installations more affordable, as illustrated by the the solid line in Panel (a) of Figure 2. Costs have declined steeply from €7,000 per kWp in 2000 to less than €2,000 per kWp in 2012. The drop in costs mainly reflects the global decline in the price of the capital inputs (solar modules, power inverters). This decline has been caused by both technological progress and higher competition due to the market entry of Asian manufacturers.

The increased feed-in tariff combined with rapidly falling costs made it profitable to invest into rooftop PV systems in most German regions. This is illustrated in Panel (b) of

Figure 3: Total Annual Installations



Note: This figure shows the total installations of PV systems (measured in MWp) with less than 500 kWp capacity by year.

Figure 2, which depicts the net present value for each kWp of credit-financed PV installations in a county with median solar radiation.[14] In counties with median radiation and above, investing into rooftop PV systems became profitable with the increase in the feed-in tariff in 2004. The steep decline in costs in 2009 made the investment very profitable, particularly before lawmakers reacted by reducing the feed-in tariff accordingly.

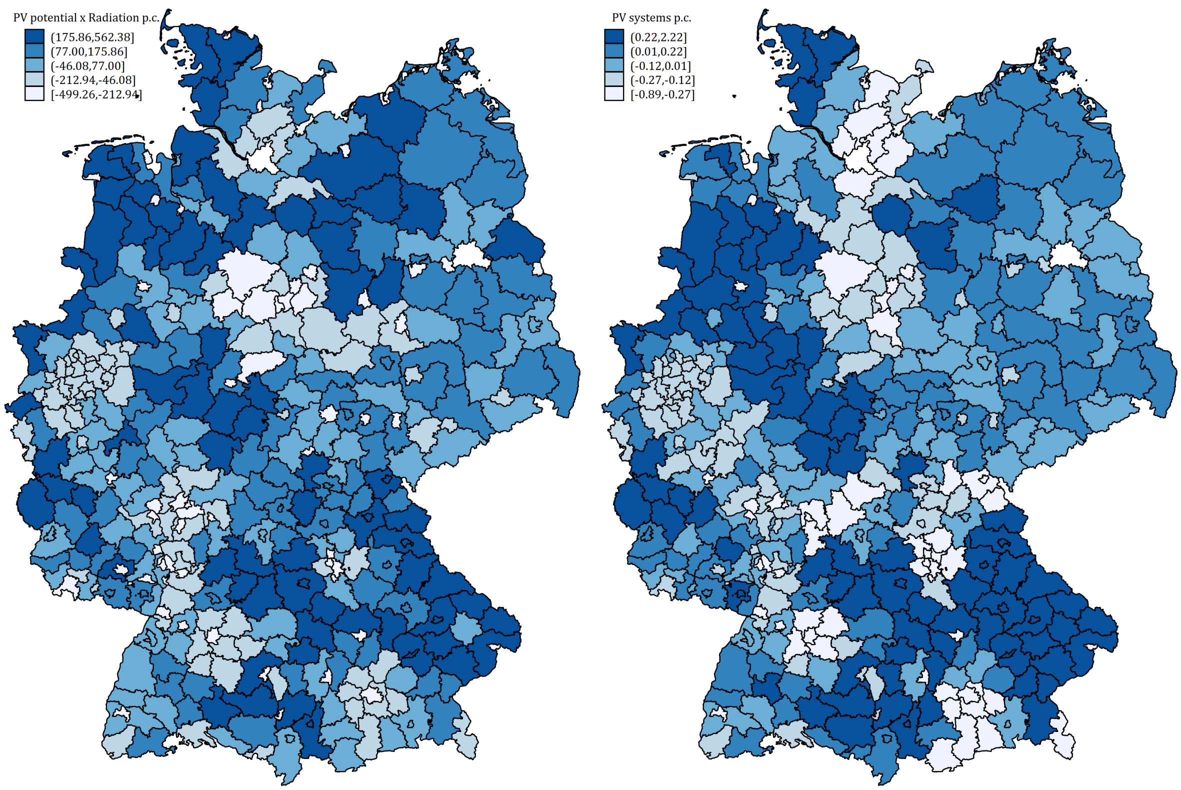
Figure 3 shows that yearly PV installations closely track the time variation in the profitability of these investments. In 2004, photovoltaic systems with 600 MWp were installed, more than in all previous years combined. After 2004, the upward trend continued until its peak in 2010, when yearly installations reached 5,000 MWp.[15]

Determinants of Investments across Space As the feed-in tariff and the costs of PV systems are (roughly) equal across German regions, the extent to which counties may benefit from installing rooftop PV systems depends on the local potential for electricity production. The latter is, in turn, a function of the local amount of solar radiation and local rooftop potential, the space available and suitable for PV installations. Because the electricity

[14] Most rooftop PV systems are, at least in part, credit financed (Bickel et al., 2008, 2009; Bickel and Kelm, 2010, 2011, 2012, 2013). We assume that the relevant interest rate for financing PV installations is similar to the one for mortgages, as the PV system and its relatively risk-free income stream can serve as collateral. The average yearly interest rate on new mortgages has fluctuated between 4 and 6.5% between 2000 and 2009, and has been dropping to below 3% between 2009 and 2012. Calculating the net present value requires additional assumptions on the performance ratio of PV systems (to quantify output) and their operating costs and depreciation (to quantify cost flows). In the following subsection, we discuss our assumptions and give the exact formula for the net present value in equation (2).

[15] For comparison, one reactor of a typical nuclear power plant produces between 500 MW and 1,500 MW of electrical power.

Figure 4: Geographic Distribution of Total Installations and Rooftop Potential × Radiation



(a) Radiation × Rooftop Potential p.c.

(b) Total Installations p.c.

Note: Panel (a) shows the geographic distribution of *rooftop potential* × *radiation* per capita (p.c.) across counties relative to their state-specific mean. Panel (b) depicts the *total power output capacity* (in kWp p.c.) installed across counties between 2003 and 2012 relative to the state-specific mean. The city-states of Hamburg (blank county in the North) and Berlin (blank county in the North-East) are excluded. The color coding scheme corresponds to quintiles of installations and *rooftop potential* × *radiation*; darker colors indicate higher values. Per capita values are normalized with the working-age population in 2003.

produced by a PV system is proportional to the product of radiation and the amount of space covered with solar panels, a county's potential gain from PV installations is proportional to the product of the county's yearly radiation (measured in kWh per square meter) and its total rooftop potential (measured in kWp).

Panel (a) of Figure 4 shows the spatial distribution of *rooftop potential* × *radiation*, normalized by the working-age population in 2003 and relative to the state-specific mean, across counties. While radiation is generally higher in the South, there is substantial variation in whether counties are more and less suitable for rooftop PV installations across all parts of Germany. Panel (b) of Figure 4, in turn, depicts the spatial variation of total capacity installed during the major expansion of installations between 2003 and 2012, normalized by the working-age population and relative to the state-specific mean, as before. Comparing the variation in *rooftop potential* × *radiation* and PV installations, it becomes clear that counties with a higher suitability for PV installations in general also experience a larger increase in their solar power capacity.

Remuneration Potential The time-varying costs and benefits of installing PV systems can be combined with the regional productivity of PV systems in producing solar energy into a single measure that captures the time-variation in local profitability of PV installations. This measure, which we call "*remuneration potential*" and which we use as an instrument for investments in Section 4.2, is the net present value of investing in PV systems with an output capacity equal to the county's rooftop potential in a given year t. Formally, the remuneration potential of county c in year t is defined as follows:

$$Remuneration\ Potential_{c,t} = Rooftop\,Potential_c \times$$
$$\left[\sum_{\tau=t}^{t+20}\left(\left(\frac{1}{1+i_t}\right)^{\tau-t}\left(\underbrace{0.995^{\tau-t}\cdot 0.75\cdot Radiation_c}_{\text{electricity produced by 1 kWp system}}\cdot Tariff_t - \underbrace{0.01\cdot Costs_t}_{\text{operating costs}}\right)\right) - Costs_t\right]. \quad (2)$$

Remuneration potential is the product of the rooftop space suitable for PV systems, measured in kWp, and the net present value of operating a PV system with output capacity of 1 kWp for 20 years from year t onwards.[16] The net present value, the term in brackets, is given by the net income stream (discounted using today's interest rate i_t) less the installation costs at t. The net income stream, in turn, equals the electricity production times the feed-in tariff, where we need to adjust the power output capacity under optimal conditions for average working conditions. Here, we follow the European Union's PVGIS and assume a performance ratio of 0.75. Following Wirth (2015), we also adjust for gradual performance losses of 0.5% per year and annual operating costs of 1% of the installation costs.[17]

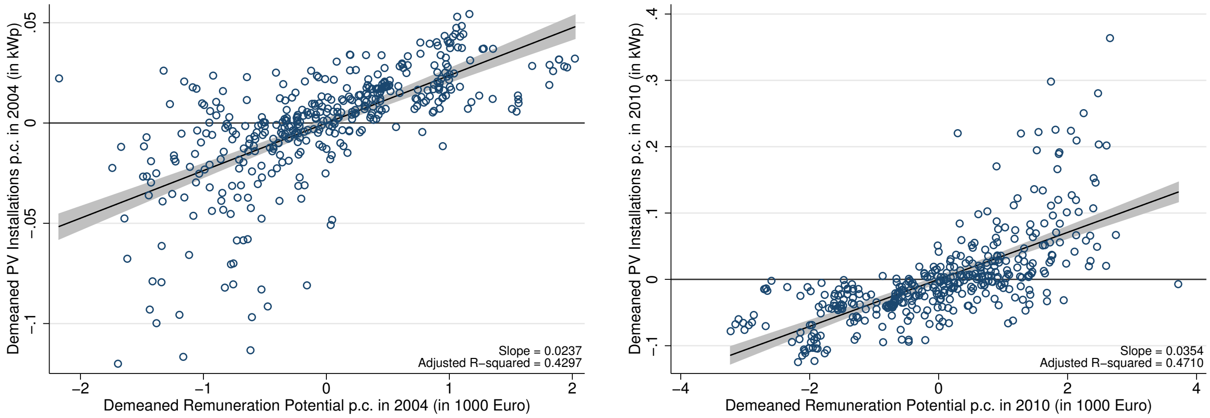
Figure 5 shows that remuneration potential is a strong predictor of investments in PV systems.[18] It plots PV installations per capita, demeaned by their 2003 to 2012 county mean and relative to the state × year average, against the similarly demeaned remuneration potential per capita. Panel (a) shows the data for the start of the PV investment boom in 2004, and Panel (b) shows the data for the peak of the boom in 2010. In both years, variation in remuneration potential explains roughly half of the variation in PV installations. The slopes imply that a €1,000 increase in per capita remuneration potential is associated with an increase in per capita installations of 0.024 to 0.035 kWp. Given the installation

[16]We assume the PV system to be operational for 20 years, as this is the time for which the feed-in tariff remains fixed.

[17]Examples of operating costs are repairs, cleaning of panels due to dust and pollen, and insurance.

[18]This echoes the formal first stage results in Appendix B.

Figure 5: Remuneration Potential and PV Installations



(a) In 2004 (b) In 2010

Note: This figure plots demeaned PV installations per capita (relative to the county and state × year specific mean) against the identically demeaned remuneration potential per capita as defined by equation (2). Panel (a) plots these data for the cross-section of counties in 2004, and Panel (b) shows the equivalent data for 2010.

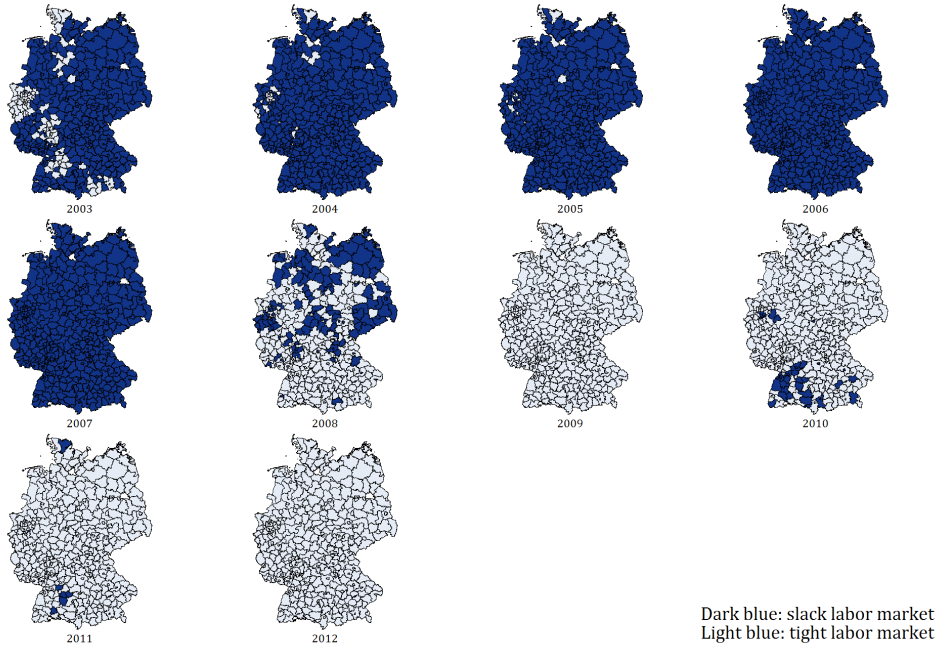
costs in 2004 and 2010, the latter correspond to additional investments worth roughly €140 and €100, respectively.

3.2 Classification of Slack and Tight Labor Markets

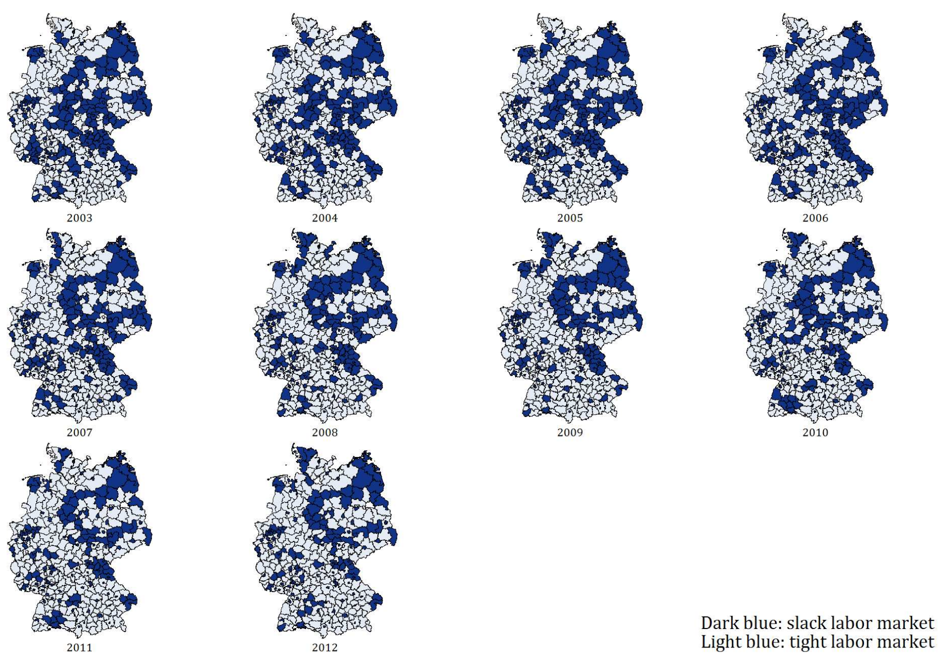
In order to investigate whether the employment effect of PV installations depends on the state of the economy, we need to define whether a labor market is "slack" or "tight." We build on the approaches of Nakamura and Steinsson (2014) and Shoag (2015). In particular, we define the state of the labor market of a county at time t as slack if the county's unemployment at time $t-1$ is above a benchmark. Otherwise, the county's labor market is defined as tight. Given this definition, the choice of the benchmark specifies in which dimension the sample is split into counties with slack and tight labor markets. For each sample split, we then estimate equation (1) separately for each subsample and formally test whether the employment effects of investments differ between the subsamples.

For the main specifications, we apply two definitions of the benchmark unemployment level that separates slack and tight labor markets. The first definition follows Nakamura and Steinsson (2014) and splits the sample along the time series dimension. This exploits the long, ten year period, during which there were stable and favorable conditions for investments in PV systems. According to this *time-series split*, a county's labor market is defined to be slack if its unemployment in the previous year is higher than the county's mean unemployment

Figure 6: Labor Market Slack across Counties



(a) Time-series Classification of Slack



(b) Cross-sectional Classification of Slack

Note: Panel (a) shows, for each year in the sample, which counties are classified as having a slack or tight labor market according to the definition of slack in the time-series dimension. Here, the labor market is defined to be slack if a county's unemployment in the previous year is higher than the mean unemployment of the county over the sample period. Panel (b) shows which counties exhibit slack / tight labor markets according to the definition of slack in the cross-sectional dimension. Here, the labor market is defined to be slack if a county's unemployment in the previous year is higher than the state average of unemployment in the previous year.

between 2003 and 2012.[19] Panel (a) of Figure 6 shows that, according to the time-series split, most counties' labor markets are defined to be slack prior to 2008 and tight thereafter. This reflects the downward sloping trend in German unemployment over the past decade.

The second definition of the unemployment benchmark follows Shoag (2015) and splits the sample along the cross-sectional dimension. According to this *cross-sectional split*, a county's labor market is defined to be slack if its unemployment in the previous year is higher than the state mean of unemployment in the same year.[20] Panel (b) of Figure 6 shows that the cross-sectional split selects a similar set of counties to have slack and tight labor markets in the different years.

The two sample splits have different implications. The time-series split compares the same set of counties at different times, so that the two samples of slack and tight labor markets, respectively, share the same structural features. The cross-sectional split compares different counties at the same time, thus holding constant all factors that may affect the employment response to investments over time (such as innovation in the production technology). Hence, differential employment effects in the sample splits along both dimensions can neither be explained by time trends nor structural features alone. To further bolster the robustness of the results with respect to the definition of slack and tight markets, Section 4.3 explores the employment response to investments for a wide range of additional definitions.

4 Results

This section presents the main findings. The empirical analysis shows that physical investments increase employment more at times and in regions with slack labor markets compared to times and regions with tight labor markets. This result holds irrespective of whether we estimate the employment effects of investments via OLS or IV, and independent of the particular definition of slack and tight labor markets.

4.1 OLS Results

Table 1 presents the OLS estimates of empirical model (1). As a benchmark, column (1) reports the average effect of physical investments in PV systems on employment for the full sample. Because both employment and installations are normalized by the working-age population, the coefficients of *installed capacity p.c.* can be interpreted as the number

[19] Formally, the labor market is said to be slack according to the time-series split if $unemployment_{c,t-1} > 1/10 \sum_{t=2003}^{2012} unemployment_{c,t}$.

[20] Formally, the labor market is said to be slack according to the cross-sectional split if $unemployment_{c,t-1}/N_{c,2003} > (\sum_{c \in state(c)} unemployment_{c,t-1})/(\sum_{c \in state(c)} N_{c,2003})$, where $N_{c,2003}$ is county c's working-age population in 2003.

Table 1: The Effect of PV Installations on Employment (OLS)

	Employment Rate				
Split along		Time series		Cross-section	
	Baseline (1)	Slack (2)	Tight (3)	Slack (4)	Tight (5)
Installed capacity p.c. (MWp)	19.98***	36.61**	2.78	37.91***	13.34**
	(6.58)	(17.09)	(3.86)	(13.83)	(6.47)
Population growth	0.37***	0.37***	0.25***	0.31***	0.40***
	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)
Construction p.c.	−0.25	−0.19	0.47	0.04	−0.23
	(0.22)	(0.14)	(0.30)	(0.21)	(0.26)
County fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
P-val slack < tight		0.017		0.036	
Jobs per €100,000	0.64	1.17	0.09	1.21	0.43
Observations	4000	2044	1956	1783	2189

Notes: The dependent variable is the average yearly employment rate (employment normalized by the working-age population in 2003) between 2003 and 2012. *Installed capacity p.c.* are yearly photovoltaic installations measured in megawatt peak (MWp) normalized by the working-age population in 2003 (indicated by "p.c." for "per capita"). *Population Growth* is the ratio of the working-age population in a given year to the working-age population in 2003. *Construction p.c.* is the number of residential and non-residential buildings completed in a given year. *P-Val slack < tight* reports the p-value of the test of the null hypothesis that the employment effect of PV installations is smaller in slack than in tight labor markets. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). Note that the observations in the cross-sectional split do not sum to 4000 due to singleton groups. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of additional jobs per MWp of PV installations. Hence, in the full sample, additional PV installations of 1 MWp capacity lead to, on average, around 20 additional jobs lasting for one year. Given the average installation costs of €3.121 million per 1 MWp capacity, this estimate implies that investments of €100,000 created 0.64 local job years, corresponding to costs per job year of €156,000.

Columns (2) and (3) report the corresponding estimates for the sample split into slack and tight labor markets along the *time series* dimension. Here, we find that at times of economic slack, additional PV installations of 1 MWp capacity lead to about 37 more job years, corresponding to 1.17 job years per investments of €100,000. This effect is 80% larger than the baseline effect in column (1). In contrast, at times of tight labor markets, the local employment effect of investments into PV systems is economically small and statistically indistinguishable from zero. Moreover, we reject the null hypothesis that the investment-induced employment gains are larger at times of tight labor markets at the five percent level;

the p-value of the respective one-sided test equals 0.017.

The *cross-sectional* split in columns (4) and (5) leads to similar results as the time series split. Here, we find that 1 MWp in PV installations leads to 38 more job years in counties with slack labor markets, while the same additional demand creates only 13 new job years in counties with tight labor markets. As before, the null hypothesis that employment gains in regions with tight labor markets are larger than in ones with slack labor markets is rejected at the five percent level.

The differences in the employment effects across the two sample splits cannot be explained by either counties' structural characteristics or time-varying changes in the relation between real demand and employment alone. While a correlation of local investments and structural labor market characteristics—such as higher investments in less sklerotic labor markets—may explain the difference in the employment effects in the cross sectional split in columns (4) and (5), such an explanation cannot account for the difference in the employment creation over time in the identical sets of counties in the time series split. Conversely, we have seen in Panel (a) of Figure 6 that local labor markets were mostly slack in the first years of the photovoltaic investment boom and tight in the later years, so that the results in columns (2) and (3) could potentially be explained by a reduction in labor demand for new installations.[21] However, changes in technology cannot account for the results for the cross-sectional split, as the latter compares different counties with slack and tight labor markets at the same time. Additionally, the next section uses an instrumental variable approach to provide additional evidence that unobserved third factors are unlikely to drive the results of Table 1.

In order to interpret the magnitude of the coefficients, it is important to note that only a fraction of the total costs of PV systems, the basis for the calculation of the costs per job year, accrue locally. Specifically, according to an industry survey in 2013, the local installation costs amount to about 20% of the total costs, while the remaining 80% are spent on solar panels and components (EuPD Research, 2013). According to anecdotal evidence from industry experts, installation firms charge an additional 10% of the total costs as a mark-up on the panels and components, so that roughly one third of the total costs contribute to local demand. Scaling our estimates accordingly, the local costs per job year equal about €50,000 for the full sample, and about €30,000 in slack labor markets.[22]

[21] Contrary to this hypothesis, conversations with industry experts suggest that there was no fundamental change to the technology for installing PV systems over time.

[22] It is difficult to translate these figures into an investment multiplier that accounts for added value along the entire value chain. While Chodorow-Reich (forthcoming) suggests a simple production function approach to translate employment multipliers like ours into a fiscal multiplier under the assumption of unresponsive monetary policy, this approach relies on constant factor shares of capital and labor in the production function. However, for the case of PV installations, the capital share in the local production function—i.e., PV installations—is likely to be much lower than the capital share in the manufacturing of

4.2 IV Results

One concern for identifying the effect of PV installations on employment is that investment decisions may depend on expected labor market dynamics via an unobserved third channel, such as local credit markets. As most rooftop PV systems are credit-financed, changes in local lending might influence both, employment and investments and thus bias the estimates in either direction.[23] For example, OLS could overestimate the effect of PV installations on employment if favorable lending conditions drive employment growth and investment. OLS could also underestimate the effect of PV installations on employment if loans for safe investments into PV systems are particularly attractive when the local economy is on a downward trajectory.

To address such concerns, we instrument local investments into PV systems by their profitability which is captured by *remuneration potential* as defined in Section 3.1. *Remuneration potential* is a function of time-varying factors (the feed-in tariff, the costs of components, mortgage rates) that are determined at the global or national level and thus unrelated to the trajectories of local labor markets, as well as by pre-determined geographic characteristics (the rooftop potential, local solar radiation) that are likely fixed over time and thus unresponsive to labor market developments as well. At the same time, *remuneration potential* strongly predicts investments, as shown in Figure 5. Taken together, the variable *remuneration potential* hence likely meets the identifying assumptions of relevance and exogeneity. Appendix B provides additional details regarding the first stage and further arguments for why the exclusion restriction is likely to hold.

Table 2 summarizes the IV estimates of the main empirical model (1). The IV results are qualitatively similar to the findings from OLS, in that the employment gains due to PV installations in slack labor markets are larger than the overall average and much larger than the employment gains in tight labor markets. At average installation costs, the estimated employment gains from physical investments imply that €100,000 in PV installations increase employment by about five job years in slack and by about one job year in tight labor markets, both in the time series and the cross-sectional split.[24] Due to these large differences, we

components. For this reason and because the exact estimation of the total welfare gains of investments into rooftop photovoltaic is beyond the scope of this paper, we abstain from performing such calculations.

[23] Financial service provision in Germany has a strong regional focus due to the nationwide presence of local savings banks (*Sparkassen*) and credit cooperation (*Volks- und Raiffeisenbanken*). In 2012, there were 423 savings banks, the area of business of which is often defined by county borders, and more than 900 credit cooperations. Statistics on the share of debt-financing of PV systems do not exist. However, the state-owned bank *Kreditanstalt für Wiederaufbau (KfW)* reports that in the years 2007 to 2012, between 42 and 74% of the yearly investments in PV systems have been at least partially backed by their subsidized loans program (Bickel et al., 2008, 2009; Bickel and Kelm, 2010, 2011, 2012, 2013).

[24] The difference in the magnitude of the OLS and IV estimates could indeed be driven by higher investment incentives in less prosperous regions that lead to a downward bias of the OLS estimates. Another part of

Table 2: The Effect of PV Installations on Employment (IV)

	Employment Rate				
Split along		Time series		Cross-section	
	Baseline (1)	Slack (2)	Tight (3)	Slack (4)	Tight (5)
Installed capacity p.c. (MWp)	52.57***	148.43***	22.60**	180.11***	30.53**
	(13.60)	(45.38)	(10.86)	(37.73)	(12.01)
Population growth	0.36***	0.36***	0.25***	0.30***	0.38***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Construction p.c.	−0.24	−0.20	0.48*	0.36	−0.25
	(0.23)	(0.14)	(0.29)	(0.30)	(0.27)
County fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
P-val slack < tight		0.003		0.000	
Jobs per €100,000	1.68	4.76	0.72	5.77	0.98
F-statistic instrument	88.21	22.11	59.15	28.43	79.66
Observations	4000	2044	1956	1783	2189

Notes: The dependent variable is the average yearly employment rate (employment normalized by the working-age population in 2003) between 2003 and 2012. *Installed capacity p.c.* are yearly photovoltaic installations measured in megawatt peak (MWp) normalized by the working-age population in 2003 (indicated by "p.c." for "per capita"). *Installed capacity p.c.* is instrumented by *remuneration potential p.c.* as defined in Section 3.1. *Population growth* is the ratio of the working-age population in a given year to the working-age population in 2003. *Construction p.c.* is the number of residential and non-residential buildings completed in a given year. *P-Val slack < tight* reports the p-value of the test of the null hypothesis that the employment effect of PV installations is smaller in slack than in tight labor markets. *F-statistic instrument* is the Kleibergen-Paap F-statistic of *remuneration potential p.c.* in the first stage. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). Note that the observations in the cross-sectional split do not sum to 4000 due to singleton groups. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

reject the hypothesis that employment is more responsive to investments in tight than in slack labor markets at the one percent level, even though the IV estimates are less precise than the corresponding OLS results. Finally, note that with Kleibergen-Paap F-statistics of the excluded instruments equal to 22 or higher, the first stage is strong in all specifications.

4.3 Alternative Classifications of Slack and Tight Labor Markets

Table 3 uses alternative classifications of slack and tight labor markets to show that our finding of differential employment effects does not crucially depend on the specific classification. Each row of Table 3 reports the results of an alternative sample split. Panel A reports the

the explanation may be that the IV estimates are, despite their strong first stage, much more noisy than the OLS estimates.

Table 3: Alternative Definitions of Slack in the Labor Market

	Slack Coeff	Slack SE	Tight Coeff	Tight SE	P-Value
	(1)	(2)	(3)	(4)	(5)
	Panel A: OLS				
Based on time variation in unemployment					
(1) **Within county mean**	36.61	17.09	2.78	3.86	0.017
(2) 2003-2007 vs. 2008-2012	47.79	16.98	1.87	3.25	0.002
Based on aggregate variation in unemployment					
(3) 2003-2012 national mean	28.23	26.35	18.69	6.93	0.362
(4) 2003-2012 state mean	49.82	18.22	11.25	6.47	0.013
(5) 2003-2012 state × county type mean	32.09	9.38	14.16	6.99	0.049
Based on cross-sectional variation in unemployment					
(6) Yearly national mean	43.01	23.60	21.22	7.30	0.186
(7) **Yearly state mean**	37.91	13.83	13.34	6.47	0.036
(8) Yearly state × county type mean	23.56	7.58	19.61	7.17	0.296
(9) State mean in 2002	31.32	12.00	12.78	6.31	0.061
	Panel B: IV				
Based on time variation in unemployment					
(1) **Within county mean**	148.43	45.38	22.60	10.86	0.003
(2) 2003-2007 vs. 2008-2012	200.21	49.30	11.45	6.44	0.000
Based on aggregate variation in unemployment					
(3) 2003-2012 national mean	142.27	73.88	32.50	12.00	0.071
(4) 2003-2012 state mean	193.67	48.04	24.54	10.68	0.000
(5) 2003-2012 state × county type mean	153.87	35.26	18.44	11.38	0.000
Based on cross-sectional variation in unemployment					
(6) Yearly national mean	131.16	53.89	44.45	14.32	0.057
(7) **Yearly state mean**	180.11	37.73	30.53	12.01	0.000
(8) Yearly state × county type mean	98.36	24.63	33.41	13.37	0.006
(9) State mean in 2002	120.52	31.05	31.98	12.58	0.002

Notes: This table presents the employment effects of PV installations in slack and tight labor markets for various alternative sample splits. Except for rows (2) and (9), the name of each row specifies a different unemployment benchmark (e.g., in row (3) the benchmark is the 2003-2012 national unemployment mean). The labor market is said to be slack if unemployment in $t-1$ is above the benchmark, and said to be tight otherwise. In row (2), labor markets are defined as being slack in 2007 and earlier, and tight in 2008 and later. In row (9), a labor market is slack if its unemployment rate in 2002 was higher than the state mean in 2002, and tight otherwise. Panel A reports the OLS results, and Panel B reports the IV results with the same model specification as in Tables 1 and 2, respectively. Columns entitled "Coeff" report the OLS/IV coefficient estimate of *installed capacity p.c.* for the subsample with slack and tight labor market, respectively. Columns entitled "SE" report the corresponding standard errors, clustered at the level of 94 spatial planning regions. The column entitled "P-Value" report the p-values of the test of the null hypothesis that the employment effect of PV installations is smaller in a slack labor market than in a tight labor market.

OLS estimates and Panel B the equivalent IV results.

Rows (1) and (7) in boldface are the baseline time series and cross-sectional splits from Tables 1 and 2, respectively. Row (2) contains an alternative time series split that defines all years 2007 and earlier as times of slack and all years 2008 and later as times of tight labor markets. Rows (3) to (5) split the sample based on unemployment benchmarks aggregated across time and space. In row (3), a county is said to have a slack labor market if its average unemployment rate in year $t-1$ is above the national unemployment mean between 2003 and 2012. Otherwise, the labor market is said to be tight. In rows (4) and (5), labor markets are classified accordingly, but with respect to the 2003-2012 state mean and the 2003-2012 state $\times$ county-type mean, respectively. Rows (6) to (9) provide alternative cross-sectional splits. In row (6), a labor market is defined as slack if its unemployment rate in $t-1$ is above the national mean in $t-1$. Rows (7) and (8) are defined accordingly. Finally, in row (9) a labor market is said to be slack if in 2002, the last year before the sample period, its unemployment rate was above the 2002 state mean, and said to be tight otherwise.

The estimated employment effects of investments in slack labor markets are above the corresponding estimates for tight labor markets in all specifications of Table 3. Except in the OLS specifications in rows (3) and (8), these differences are economically meaningful with the employment gains in slack market conditions being at least twice as large as the ones in tight conditions. The coefficients are statistically different from each other on conventional levels in all but three of the 16 specifications.

Taken together, we consistently find that more jobs are created at times and in regions with slack labor markets than with tight labor markets. This empirical pattern is present irrespective of the exact definition of labor market slack and robust to using an IV strategy instead of OLS.[25]

5 Discussion of Mechanisms

There are several potential explanations for the empirical pattern of fewer jobs being created locally when the labor market is tight. First, there may be a larger incentive to substitute labor with capital. Second, installation firms might meet their labor demand with hiring workers from outside the local labor market. Third, investment in tight labor markets might lead to crowding out, as in Michaillat (2014). Workers installing PV systems might be drawn from other jobs if the labor market is tight, while they might have been unemployed if the labor market is slack. Finally, there may be direct effects of labor market tightness on the

[25] In Appendix C we provide additional robustness checks regarding data choices and inclusion of additional covariates.

costs of investment (e.g., due to higher wages for installation workers or higher markups) implying a lower effective labor demand for each Euro invested in a tight labor market. However, the latter effect cannot play a role here, as we use the physical investment volume as explanatory variable.

The first channel, a substitution of labor with capital in tight labor markets, is unlikely to drive the results in the context of investment in photovoltaics. The production function of installing PV systems has been stable over the entire time period. The production process mainly consists of workers carrying photovoltaic panels onto rooftops and mounting them there, with little scope for different installation techniques. The only substitute technology available are telehandlers that can lift the panels onto roofs, which still require extensive manual labor to mount and install the system. Unfortunately, we do not have data on the usage of telehandlers and hence we provide indirect evidence that the usage of telehandlers is unlikely to account for the differences in employment gains in slack and tight labor markets.

To this end, we partition total employment into in employment in (i) high exposure industries, (ii) local non-tradables, and (iii) all other industries. The high exposure industries are directly affected by the demand for PV installations, such as electricians.[26] We classify the retail and wholesale sector, the hospitality industry (hotels and restaurants) as well as financial service providers as local, non-tradable services that may experience local demand spillovers from the high-exposure sectors. All remaining industries are classified as belonging to "other industries."[27] If it were the case that the difference in slack versus tight labor markets was driven by changes in the installation technology, we would expect that the differential response is entirely driven by differences in employment gains in the high exposure industries. Employment creation in local non-tradable industries should not exhibit differential effects, as the labor-saving technology is specific to the installation of PV systems.[28]

Table 4 reports the OLS estimates of the employment gains due to PV installations in slack and tight labor markets for each of the three sectors. Panel A presents the results for

[26]For classifying industries as being "high exposure," we take a random sample of firms that are a member of the *Bundesverband Solarwirtschaft* (a trade association of the German solar industry) that install PV systems and consult their Creditreform company profiles to extract their industry classification. Most of the sampled firms are certified electricians; as such, they belong to various industries, including building installation and engineering. The union of the industry codes identified by this procedure constitutes the set of high exposure industries.

[27]"Social services" (industry code 853) is excluded from "other industries" for two reasons. First, the employment data in this industry is non-stationary, as it increases from 4.4% to 6.2% of the workforce from 2003 to 2012. Second, this sector mostly comprises of the daycare industry (care of elderly and children), and it is unclear whether these are local services or, indeed, "other industries." Table 6 in Appendix A.1 lists the assignment of industry codes to each of the three subsectors.

[28]Note that this additionally assumes that the spillovers from the high exposure to the local non-tradable sectors do not change with the state of the labor market.

Table 4: Sectoral Employment Conditional on Slack: OLS Results

	Industry-specific Employment p.c.					
	High-exposure		Local		Other	
	Slack (1)	Tight (2)	Slack (3)	Tight (4)	Slack (5)	Tight (6)
	Panel A: Time Series Split					
Capacity p.c. (MWp)	17.95***	2.97**	7.67**	3.94***	20.98	−4.39
	(6.49)	(1.37)	(3.87)	(1.23)	(23.76)	(3.29)
P-val slack < tight	0.012		0.162		0.136	
Jobs per €100,000	0.58	0.10	0.25	0.13	0.67	−0.14
Observations	2044	1956	2044	1956	2044	1956
	Panel B: Cross-Sectional Split					
Capacity p.c. (MWp)	17.10**	11.45***	15.18***	6.64***	5.94	−5.45
	(8.37)	(4.18)	(3.16)	(2.54)	(15.94)	(8.47)
P-val slack < tight	0.220		0.008		0.211	
Jobs per €100,000	0.55	0.37	0.49	0.21	0.19	−0.17
Observations	1783	2189	1783	2189	1783	2189
PopGrowth & construction	yes	yes	yes	yes	yes	yes
County fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Note: The dependent variable in columns (1) and (2) is employment in the high-exposure sectors (construction and related industries) normalized by the working-age population in 2003 (indicated by "p.c." for "per capita"). The dependent variable in columns (3) and (4) is employment p.c. in local, non-tradable industries (wholesale, retail, hospitality, local services). The dependent variable in columns (5) and (6) is employment p.c. in all remaining industries. Employment by industry is measured annually on June 30th. Table 6 in Appendix A.1 provides details of the industry classifications. *Capacity p.c.* are yearly photovoltaic installations measured in megawatt peak (MWp). Except for the dependent variables, the empirical specifications are identical to the ones in Table 1. In particular, the *year fixed effects* are estimated at the level of the state × county type (rural or urban county). Panel A reports the results for the time series split, and Panel B reports the results for the cross-sectional split. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the time series split, and Panel B presents the results for the cross-sectional definition of labor market slackness. The first finding from Table 4 is that in both slack and tight labor markets, PV installations led to a statistically significant increase in employment only in the high-exposure and local non-tradable sectors. In contrast, the employment gains (or losses) in all other sectors are very imprecisely estimated. Given the nature of the investments we study, this is exactly the pattern of employment gains across industries which we expect to find.[29]

A second result from Table 4 is that the difference of the employment gains in slack and tight labor markets is driven by differential employment gains both in high exposure and local non-tradable industries. In the time series as well as the cross-sectional split, the difference in the employment gains between slack and tight labor markets is sizable, and, in two cases, significantly different from each other.[30] This speaks against adjustments in the production technology of PV installations conditional on the state of the labor market as an explanation for the differential employment gains in slack and tight labor markets.

The second channel, hiring workers from outside the local labor market (a county in our setting), is also unable to fully explain our findings. First, we control for population growth in all of our regressions, which should capture migration as long as workers also change their place of residence. Second, migration and commuting across space cannot explain the results of our time-series split, given that almost all counties exhibit slack and tight at the same time. Third, we show next that there is no evidence for any demand spillovers across regions independent of the state of the labor market, implying that counties in this setting are indeed self-contained labor markets with very limited cross-border movements.

To test for geographic spillovers, we follow the approach of Acconcia et al. (2014) and include investments in neighboring counties as an additional control variable. We consider three possible definitions of neighboring counties: all other counties within the same spatial planning region (*Raumordnungsregion*), the five closest counties based on the distance between both counties' most populous municipalities, and the ten closest counties. For each set of a county's neighbors we calculate the total PV installations in MWp within the set of neighboring counties and normalize the total installations with the working-age population in the county of interest. Given this, we estimate an extended version of the main empirical model (1) that includes aggregate PV installations in neighboring counties as an additional covariate. As in the main empirical analyses, we classify counties as having slack or tight

[29]This mirrors the result for the full sample of counties in Table 14 of Appendix D.1, where we find that around 60% of the entire employment effect originate from the high-exposure sectors, while 40% originate from local industries.

[30]Note that the corresponding IV results reported in Table 16 of Appendix D.2 mirror the findings from OLS shown here.

labor markets according to their own unemployment rate as described in Section 3.2.

Table 5 reports the OLS estimates of the demand spillovers conditional on the state of the labor market as defined via the time series split (Panel A) as well as the cross-sectional split (Panel B). In both splits and in all three definitions of a county's set of neighbors, the effect of additional PV installations in geographically proximate regions is at least one order of magnitude smaller than the effect of additional installations within the county. In addition to their small magnitude, all the coefficients are statistically insignificant. The estimated effects of the demand spillovers also do not differ by much between slack and tight labor markets, while the differences of the employment gains due to the within-county investments remain at the same level as in Table 1, the main OLS specification.[31] All in all, we hence conclude that the employment effects of PV installations are very local in nature, so that demand spillovers are largely unimportant for the interpretation of our findings.

Taken together, this leaves crowding out as the most plausible mechanism. Workers installing PV systems might be drawn from other jobs if the labor market is tight, while they might have been unemployed if the labor market is slack. This is the mechanism identified by Michaillat (2014), who argues that the employment response to additional demand is a general function of the state of the labor market. In his search and matching model, diminishing returns to labor lead to a quasi-labor supply curve that is convex in labor market tightness, so that additional labor demand leads to a higher degree of crowding out in a tight than in a slack labor market. Our empirical results are consistent with this notion.

6 Conclusion

In this paper, we use the case of investment in photovoltaics in Germany to understand how job creation depends on the state of the labor market. This setting is ideally suited to inform this question as €64 billion were invested over ten years across 400 counties, yielding ample variation in the identical type of investment in different states of the local labor market. Furthermore, plausibly exogenous differences in local profitability allow us to construct an instrumental variable for investment.

We find that investment in photovoltaics creates many more jobs in time periods and regions with slack than with tight labor markets. Our result has two main implications. First, investments during a recession pay a double dividend as they put additional people to work, while they mostly lead to crowding out in booms. Hence, economic downturns are a good time to undertake public investment programs. Second, place-based policies provide a better

[31] Appendix D.1 shows that there is no evidence for demand spillovers in the full sample either, and Table 17 in Appendix D.2 demonstrates that the IV estimates lead to the same conclusions as the OLS estimates.

Table 5: Spillovers from Neighboring Counties: OLS Results

	Employment Rate					
	Planning Region		5 Closest Counties		10 Closest Counties	
	Slack (1)	Tight (2)	Slack (3)	Tight (4)	Slack (5)	Tight (6)
	Panel A: Time Series Split					
Capacity p.c. (MWp)	32.58**	2.09	34.29**	2.81	32.80**	1.75
	(16.39)	(4.04)	(15.79)	(4.38)	(16.23)	(4.29)
Neighboring capacity p.c.	3.05	0.43	0.72	−0.01	0.91	0.23
	(2.66)	(0.75)	(1.67)	(0.74)	(0.69)	(0.39)
P-val slack < tight	0.024		0.017		0.020	
Jobs per €100,000	1.04	0.07	1.10	0.09	1.05	0.06
Observations	2044	1956	2044	1956	2044	1956
	Panel B: Cross-Sectional Split					
Capacity p.c. (MWp)	42.25***	13.45**	41.54***	15.35***	37.98***	15.55***
	(11.20)	(6.54)	(12.18)	(5.84)	(10.28)	(5.90)
Neighboring capacity p.c.	−0.86	−0.10	−0.67	−0.86	−0.01	−0.59
	(0.93)	(2.06)	(0.88)	(1.33)	(0.57)	(0.64)
P-val slack < tight	0.010		0.022		0.024	
Jobs per €100,000	1.35	0.43	1.33	0.49	1.22	0.50
Observations	1783	2189	1783	2189	1783	2189
PopGrowth & construction	yes	yes	yes	yes	yes	yes
County fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Note: *Neighboring capacity p.c.* is the sum of PV installations (measured in MWp and normalized by the working-age population) across all other counties in the same spatial planning region (columns (1) and (2)), the 5 closest counties (columns (3) and (4)), or the 10 closest counties (columns (5) and (6)). Closeness is measured by the distance between the counties' most populous municipalities. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). All other variables are defined as in Table 1. Panel A reports the results for the time series split, and Panel B reports the results for the cross-sectional split. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

return in terms of jobs in regions with high unemployment than with low unemployment.[32] This suggests that the design of make-work programs should take economic circumstances of targeted areas into account, even if we ignore all equity concerns.[33]

We are able to identify the state-dependent employment gains of investment programs by exploiting that investment in photovoltaics is comparable across time and space. In addition, our results from the German setting are informative for policy discussions surrounding similar investment programs in photovoltaic energy around the world. Although the primary aim of these programs is to increase renewable energy production, our results show that they may also cause substantial employment gains, at least in slack labor markets.

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[32] This finding is echoed by Austin et al. (2018).

[33] Note, however, that such targeting of investment also has potential costs. First, investment in high unemployment regions might encourage workers to stay in that region instead of moving to places with higher productivity (Kline and Moretti, 2013). Second, if recessions have a cleansing effect, investing in downturns might reduce the exit of unproductive firms and thus enhance the misallocation of capital (e.g., Foster et al., 2016).

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Appendix (for Online Publication)

A Appendix to Section 2: Data

A.1 Data Sources and Definitions

Table 6: Data Sources and Definitions

Variable	Description	Source
Dependent Variables		
Employment rate	Employees subject to social security contributions in the county of residence normalized by the working-age population.	Federal Employment Agency (*Bundesagentur für Arbeit*)
Employment p.c. in high-exposure sectors	Employees subject to social security contributions in the county of residence in photovoltaic-related industries (industry codes 31, 321, 332, 401, 453, 454, 518, 519, 524, 731, 742, 743) of the German Classification of Economic Activity, Version 2003, normalized by the working-age population. The set of industry codes is the union of industry codes of a random sample of firms that are members of the German Solar Association (*Bundesverband Solarwirtschaft*). From 2008 onwards, the original data is classified following the revised German Classification of Economic Activity, Version 2008. We cross-walk the data from the industry classification in 2008 into the industry classification of 2003 following the official correspondence table.	Employment data at the three-digit industry level purchased from the Federal Employment Agency. Correspondence table here.
Employment p.c. in local services	Employees subject to social security contributions in the county of residence in local, non-tradable industries (wholesale and retail–industry codes G except 518, 519, 524; hospitality–industry code H; and financial services–industry codes 651, 652) of the German Classification of Economic Activity, Version 2003, normalized by the working-age population. The data from 2008 onwards follows a revised industry classification. Converted into the industry classification as of 2003 as described above.	Employment data at the three-digit industry level purchased from the Federal Employment Agency. Correspondence table here.

Variable	Description	Source
Employment p.c. in other sectors	Employees subject to social security contributions in the county of residence in all the industries not included in "high-exposure sector," "local services," and except social services (industry code 853), normalized by the working-age population. The data from 2008 onwards follows a revised industry classification. Converted into the industry classification as of 2003 as described above.	Employment data at the three-digit industry level purchased from the Federal Employment Agency. Correspondence table here.
Working-age population	The population of working age (between 15 and 65 years of age) in 2003. In our analysis, most variables are normalized by the working-age population (indicated by "p.c." in the variable name).	German Statistical Office, population statistics (code 173-21-4)
Photovoltaic Investments, Instruments, and Classification of Tight / Slack Labor Markets		
Photovoltaic installations (in MWp)	Capacity and location of each photovoltaic system in Germany measured in MWp and day of connection to the energy grid. We aggregate capacity from the project lists using county and municipality identifiers.	Deutsche Gesellschaft für Sonnenenergie; project lists here.
Rooftop potential	Estimates of rooftop space based on the aerial maps of 4500 dwellings; see Appendix A.2 for details.	Lödl et al. (2010)
Solar radiation	Yearly average global irradiance on the optimally inclined surface.	PVGIS project of the European Union
Feed-in tariff	Guaranteed price per kWh of produced electricity for installations with an output capacity of less than 30 kWp.	Renewable Energy Act
Costs of solar installation	Industry survey on total installation costs per kWp.	Janzing (2010); Bundesverband Solarwirtschaft e.V. (2012, 2014)
Interest rate	Average interest rate on mortage loan (prior to 2003), effective interest rates of commercial banks for housing loans.	Bundesbank (series BBK01.SU0010 and BBK01.SUS131)
Ownership structure	Buildings by type of ownership: multiple ownership, private person, housing cooperative, region or state, municipal housing companies, private housing company, other private companies and non-profits.	Housing questionnaire of the Census 2011

Variable	Description	Source
Unemployment rate	Individuals receiving unemployment benefits in the county of residence normalized by the working-age population. At the state and national level, we compute the unemployment rate as the sum of unemployed individuals divided by the sum of the working-age population.	Federal Employment Agency
Control Variables		
County type	Counties comprise either of a single municipality (so-called city counties or *Kreisfreie Städte*) or multiple municipalities (so-called rural counties or *Landkreise*).	Federal Office for Building and Regional Planning (*Bundesamt für Bauwesen und Raumordnung*)
Population growth	The ratio of the working-age population in any given year and the working-age population in 2003.	German Statistical Office, population statistics (code 173-21-4)
Construction	The number of residential and non-residential buildings completed in a given year.	German Statistical Office, construction statistics of completed buildings (code 311-21)
Total area, settlement and dwelling area	The total area of a county in km^2 as of 2008. Includes data on the usage of data for settlement, dwellings and in eleven other categories.	German Statistical Office, area statistics (code 331-11)
Square meters (living area)	Floor space in residential buildings. Data is measured on 31.12.2008.	German Statistical Office, housing statistics (code 035-21-5)
Apartments/building	Number of apartments per residential building. Raw data gives number of buildings with 1, 2 or more apartments. For the last category an average of six apartments per building is assumed. Data is measured on 31.12.2008.	German Statistical Office, housing statistics (code 035-21-5)
Population / population density	Total population, measured on 31.12.2008. Population density is population per area in km^2.	German Statistical Office, population statistics (code 173-01-5)

Variable	Description	Source
Education shares	Employment Shares by Education. The ratio of employees with a university degree to the total number of employees and the ratio of employees with vocational training to the total number of employees as of Q2 2003. The baseline is the share of employees with less education than vocational training.	Federal Employment Agency
Industry shares	A vector of three variables, all as of Q2 2003: the share of employees in agriculture (industry codes 01–03), the share of employees in manufacturing (industry codes 05–39), and the share of employees in construction (industry codes 41–43). The omitted category is the share of employees in services (industry codes 45–95).	Employment data at the three-digit industry level purchased from the Federal Employment Agency
School & university students p.c.	The official statistics provide the numbers of school students for ten different school types. We use the sum across all school types.	German Statistical Office, school statistics (code 192-32-4)
	Both the number of school students and the number of university students are measured in 2003 and normalized by the working-age population.	University statistics of the German Rectors' Conference (*Hochschulrektorenkonferenz)*
Solar panel manufacturer	Locations of the establishments of German solar panel and components manufacturers.	EEM Energy & Environment Media GmbH

Redistricting The administrative boundaries of counties changed in three East German states (Saxony-Anhalt in 2007, Saxony in 2008, Mecklenburg-West Pomerania in 2011) during the sample period. These reforms took place in response to declining rural population in East Germany and mainly merged several former counties into a single one in order to save administrative costs. We recalculate all the variables from before the administrative reforms to the level of the county boundaries after the reform. All but three former counties are completely merged into new counties, so that the aggregation of these data is straightforward. For the three counties, whose municipalities are assigned to two or three new counties (*Demmin*, county code 13052, in Mecklenburg-West Pomerania, and *Zerbst/Anhalt*, county code 15151, as well as *Aschersleben-Staßfurt,* county code 15352 in Saxony-Anhalt), we disaggregate each statistic based on the relative population shares before the county merger. That is, if the old county A is split to merge into the new counties B and C and if 2/3 of the pre-reform population of county A will be assigned to county B (leaving 1/3 for county

C), we construct (virtual) counties B and C before the reform by assigning 2/3 of the value of each statistic (e.g., employment in manufacturing) from county A to the (virtual) county B and 1/3 of the value of each statistic to the (virtual) county C.

A.2 Estimation of Rooftop Potential

Following the approach of Lödl et al. (2010) we estimate the rooftop potential for each county in Germany with the following three steps:

1. We classify each German municipality according to the five criteria in Table 7 into four types: very rural, rural, suburban or urban.

2. In a next step, we multiply the settlement area of each municipality with the estimated roof-top potential per km^2 of settlement area by municipality type. Lödl et al. (2010) calculate the average rooftop potential for each municipality type shown in Table 7 based on aerial maps of Bavaria and assumptions on roof angles and exposition.

3. In a last step, we aggregate the estimates of rooftop potential of all municipalities to the county level.

Table 7: Estimating Rooftop Potential Following Lödl et al. (2010)

Category	Very Rural	Rural	Suburban	Urban
Thresholds for Classification				
Population	≤ 2000	≤ 5000	≤ 20000	> 20000
Population density (per km^2)	≤ 100	≤ 200	≤ 300	> 300
Settlement area (in km^2)	≤ 0.4	≤ 0.8	≤ 1.5	> 1.5
Living area p.c. (in m^2)	> 48	> 45	> 42	≤ 42
Number of apartments	≤ 1.4	≤ 1.6	≤ 1.8	> 1.8
Rooftop Potential Estimates from Lödl et al. (2010)				
Settlement area per dwelling (in m^2)	3734	1793	795	795
Rooftop potential per dwelling (in kWp)	25.8	13.9	5.7	0.25×5.7
Number of Municipalities				
N	4413	3997	1854	946

B Appendix to Section 3: Empirical Strategy

Section 3 points out that *remuneration potential* as described in Section 3.1 can serve as an instrument for investments in rooftop PV systems. Section 4.2 presents the main results when estimating the empirical model (1) using *remuneration potential p.c.* as an instrument for *installed capacity p.c.* of rooftop systems. The IV strategy serves as a check for whether unobserved factors drive our results. In this section, we discuss the two main IV assumptions, relevance and exogeneity.

Relevance and First Stage

Table 8 shows that the time variation in remuneration potential at the county level is a strong predictor of annual PV installations. For the pooled sample of all German counties in column (1), an increase in the remuneration potential of €1 million led to additional PV installations of 0.023 MWp (or 23 kWp) on average, similar to the coefficients for the years 2004 and 2010 in Figure 5. Given the (weighted) average price of installations of €3,121 per kWp, this implies additional investments of about €72,000. Comparing counties with and without slack labor markets, the average change in investments in response to changes in the remuneration potential tends to be smaller if the labor market is classified as being slack, both according to the time series and the cross-sectional definition. Nevertheless, even then a €1 million increase in remuneration potential leads to additional PV installations of at least 8 kWp, corresponding to investments of around €25,000. Moreover, these effects are precisely estimated, so that the remuneration potential is a strong instrument with Kleibergen-Paap F-statistics of 22 and higher, well above the critical value of 10.

Exclusion Restriction

The exclusion restriction requires that conditional on covariates, the instrument does not directly influence employment outcomes. In particular, the instrument is not allowed to influence local employment over and above the common employment trends that is filtered out by the time fixed effects at the state $\times$ county-type level. While this assumption is untestable, it is unlikely that any of the factors that drives the variation in the remuneration potential directly affects the county-specific employment outcomes.

For one, there is no indication for the existence of direct feedback effects between the time-varying components of the remuneration potential (feed-in tariff, installation costs, interest rates) and the heterogeneous local employment outcomes net of the time fixed effects. The feed-in tariff is chosen at the national level in order to ensure a certain volume of renewable energy production, in line with the aim of the Renewable Energy Act. Accordingly, the feed-in tariff has been adjusted in response to total installed capacity, either by amendments of the law (in 2009) or directly linked to the level of past installations by law (from 2009 onwards). The feed-in tariff has never been altered in response to labor market conditions in particular

Table 8: First Stage

Split along	Installed Capacity p.c. (in MWp)				
		Time series		Cross-section	
	Baseline (1)	Slack (2)	Tight (3)	Slack (4)	Tight (5)
Remuneration p.c. (Mio €)	0.0232***	0.0077***	0.0259***	0.0090***	0.0304***
	(0.0025)	(0.0016)	(0.0034)	(0.0017)	(0.0034)
Population growth	0.0003***	0.0001	0.0001	0.0001	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Construction p.c.	0.0026*	0.0007	0.0025	−0.0016	0.0048**
	(0.0015)	(0.0005)	(0.0025)	(0.0015)	(0.0020)
County fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
F-statistic instrument	88.21	22.11	59.15	28.43	79.66
Observations	4000	2044	1956	1783	2189

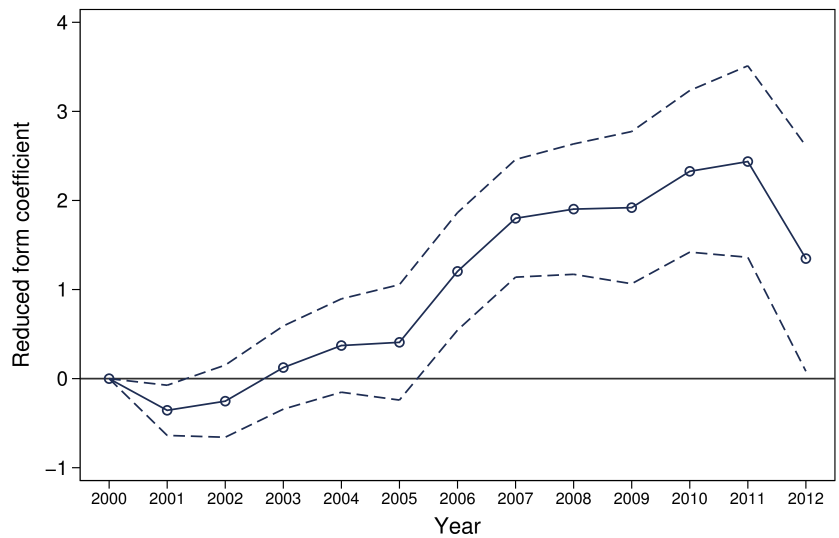
Note: The dependent variable *installed capacity p.c.* are photovoltaic installations measured in megawatt peak (MWp) normalized by the working-age population in 2003 (as indicated by "p.c." for "per capita"). *Remuneration p.c.* is the remuneration potential for PV systems of the size of the county's rooftop potential, given local solar radiation, the current installation costs, and the applicable feed-in tariff. *Population Growth* is the ratio of the working-age population in a given year to the working-age population in 2003. *Construction p.c.* is the number of residential and non-residential buildings completed in a given year. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). *F-statistic instrument* is the Kleibergen-Paap F-statistic of the instrument (*remuneration potential p.c.*). Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

counties or states. Similarly, the changes in the national average costs of PV installations are mainly driven by conditions on the world market for solar panels, which is dominated by Asian manufacturers.[34] In Appendix C we also show that the results are unaffected by excluding those counties that host establishments of German solar panel manufacturers. Finally, the mortgage rate tracks the ECB refinancing rate, which is set for the Euro zone as a whole irrespective of the idiosyncratic labor market conditions in specific German counties.

The exclusion restriction also fails if the cross-sectional variation in *rooftop potential* × *radiation* is correlated with labor market dynamics. Yet, it is unlikely that the stock of housing foreshadows local labor market dynamics. According to the German Census of 2011, 87.9% of private houses were built before 2000 and 95% before 2004. Rooftop potential was hence largely fixed before the photovoltaic investment boom between 2004 and 2012. To alleviate the potential concern that our estimates pick up effects from construction

[34]Between 2000 and 2013, the share of German manufacturers in world solar cell production has never exceeded 20%, while Asian manufacturers produced at least 48% (http://www.earth-policy.org/data_center/C23, last accessed on April 5th 2018).

Figure 7: Reduced Form Coefficient of Rooftop Potential × Radiation over Time



Note: The connected circles show, for each year between 2001 and 2012, the average differences in employment relative to 2000 for each 1,000 MW of potential peak solar energy production (as measured by the product of rooftop potential and radiation). The 90 percent confidence intervals are plotted as dashed lines. The estimates are obtained from the model described in Footnote 35.

nevertheless, we directly control for construction activity in all regressions. Solar radiation, in turn, is unlikely to have a direct impact on labor markets. The climate is temperate across all German regions so that potential effects of heat on labor productivity (e.g. Dell et al., 2012) are irrelevant.

Figure 7 provides a plausibility check for whether the cross-sectional variation in *rooftop potential* × *radiation* is correlated with employment via channels other than photovoltaic installations. It displays the reduced form effect of *rooftop potential* × *radiation* on employment, that is, the average increase in employment relative to 2000 for each 1,000 MW of potential peak solar energy production.[35] The exclusion restriction implies that *rooftop potential* × *radiation* affects employment only via PV installations. The magnitude of the

[35]Formally, Figure 7 displays the estimates $\hat{\gamma}_t$ of the following regression:

$$\begin{aligned} Employment\, p.c._{c,t} = &\sum_{t=2001}^{2012} \gamma_t \left(Rooftop\, Potential_c \cdot Radiation_c\, p.c._c \right) \cdot \mathbb{1}[Year_t] \\ &+ CountyFE_c + \tilde{\delta}_{c,t}\, \mathbb{1}[Year_t \times State_c \times CountyType_c] + Controls_{c,t} + \epsilon_{c,t}. \end{aligned}$$

Rooftop Potential$_c$ · Radiation$_c$ $p.c._c$ is the product of a county's potential for rooftop photovoltaic installations (measured in 1,000 MWp) and the county's average solar radiation, normalized by the county's working-age population. As such, it measures the potential yearly energy production in 1,000 MWp under optimal conditions, if the entire available suitable roof space was covered by PV systems. All other variables are as defined in equation (1).

estimated employment effects are hence expected to track the overall time path of photovoltaic investments displayed in Figure 3. The results in Figure 7 support this hypothesis. The employment gains predicted by *rooftop potential* $\times$ *radiation* become statistically and economically different from zero only after the start of the photovoltaic investment boom in 2004, peak at the height of the boom in 2010 and 2011, and drop in 2012 mirroring the drop in investments in this year.

C Robustness to Section 4: Main Results

This section evaluates the robustness of the main finding that the employment gains of investments are larger when the labor market is slack compared to when it is tight, both for our OLS and our IV specification.

C.1 OLS Results

For brevity, each row in Table 9 documents the result for a different specification and reports the OLS estimates for the observations with slack and tight labor markets according to both the time series and cross-sectional classifications of the state of the labor market. Columns entitled as "Coeff" report the coefficient estimates for the relevant sample, and columns entitled "SE" present the corresponding standard errors clustered at the level of 94 German spatial planning regions (as in the main specification). The columns "P-Val" contain the p-values of the test of the null hypothesis that the effect of PV installations on employment is smaller in slack than in tight labor markets. For comparison, row (0) reports these statistics for the corresponding empirical specifications from Table 1.

Determinants of Rooftop Potential The first set of robustness checks adds those variables as additional covariates that are components of the highly non-linear estimate of rooftop potential used for constructing the instrument (see Appendix A.2 for details on the estimation of rooftop potential following Lödl et al., 2010). These variables are geographic characteristics of counties and their municipalities that exhibit little time variation, but that are strongly correlated with total PV installations. We test whether these characteristics are correlated with employment dynamics as well by holding them constant as measured in 2008 (exactly as in the estimation of rooftop potential) and interacting them with year dummies.

Different measures of a county's area constitute the first type of variable used for the estimation of rooftop potential. In addition to the standard covariates, row (1) controls for total county area, row (2) controls for total settlement area (area designated to buildings and transport), and row (3) controls for total dwelling area (area designated to buildings).

Table 9: Robustness: OLS

	Time series split					Cross-sectional split				
	Slack		Tight		P-Val	Slack		Tight		P-Val
	Coeff	SE	Coeff	SE		Coeff	SE	Coeff	SE	
(0) Baseline	36.61	17.09	2.78	3.86	0.017	37.91	13.83	13.34	6.47	0.036
Determinants of Rooftop Potential										
(1) Area × year	33.62	20.04	−0.35	4.22	0.036	37.04	14.32	16.33	7.47	0.073
(2) Total settlement area × year	36.37	17.26	3.15	3.92	0.019	40.49	14.70	13.39	6.47	0.029
(3) Total dwelling area × year	35.46	17.20	4.04	3.92	0.024	39.88	14.87	12.00	6.72	0.028
(4) Population density × year	30.96	16.55	0.05	3.72	0.023	33.45	12.88	10.49	6.28	0.033
(5) Square meters p.c. × year	29.79	16.49	−0.88	3.88	0.024	35.17	13.67	10.46	6.71	0.036
(6) Apartments/building × year	16.58	15.24	−2.17	3.71	0.092	21.28	9.62	7.80	6.63	0.086
Structural Characteristics										
(7) Education share × year	28.55	16.88	4.23	4.61	0.057	39.79	13.65	18.52	7.13	0.048
(8) School & uni students × year	29.31	16.14	1.25	3.97	0.030	36.28	13.58	10.12	6.70	0.023
(9) Industry share × year	31.09	15.57	−2.09	4.95	0.010	31.21	12.84	14.10	7.81	0.084
(10) Industry & education share × year	28.32	15.22	−0.45	4.87	0.017	30.86	12.70	14.38	7.70	0.087
Model Specification										
(11) Investments uncleaned	14.60	10.76	−1.24	1.03	0.070	4.61	2.06	4.35	3.03	0.469
(12) Without solar panel manufacturers	31.24	18.05	1.42	3.88	0.039	38.30	14.28	14.08	7.13	0.043
(13) Only city counties	71.25	43.62	−3.62	22.21	0.067	24.73	21.63	36.90	33.31	0.632
(14) Only rural counties	30.66	14.96	1.85	3.76	0.018	22.13	7.67	13.60	6.67	0.123

Notes. This table presents the results of various modifications of the baseline specification of Table 1. It provides OLS estimates of the employment effect of PV installations conditional on the state of the labor market according to both the time series and the cross-sectional split of the sample. Each row of the table represents the result of a different modification of the baseline specification; see the text for details. Columns entitled "Coeff" report the OLS coefficient estimate of *installed capacity p.c.* for the subsamples with slack and tight labor market, respectively. Columns entitled "SE" report the corresponding standard errors, clustered at the level of 94 spatial planning regions. Columns entitled "P-Val" report the p-value of the test of the null hypothesis that the employment effect of PV installations is smaller in a slack labor market than in a tight labor market.

The second determining factor for the measure of rooftop potential is population density, for which we control in row (4). The final set of variables concerns housing, with the square meters of housing per individual of working age being an additional covariate included in row (5), and the average number of apartments per residential building being added in row (6). Overall, none of the additional covariates changes the results substantially, suggesting that there is no single cross-sectional determinant of PV installations that explains away the main findings. That being said, the addition of the number of apartments per building has the largest effect on the results, leading to a drop in the coefficients by at least one third. A potential reason for this is that the number of apartments per building are strongly correlated with the ownership structure of housing.[36] As installing PV systems requires unanimous consent of all owners of a building, a diverse ownership structure increases the transaction costs of the investment decision, leading to lower investments. As a consequence, the number of apartments per building, via their strong correlation with the ownership structure, is a strong predictor of PV installations, and hence absorbs parts of their employment effects.[37] Nevertheless, even with the number of apartments per building as an additional covariate, the p-value of the null hypothesis that the effect of investments on employment is larger in tight than in slack labor markets remains below 0.1.

Structural Characteristics The second set of robustness checks explores whether controlling for structural characteristics alters the results. As for the determinants of rooftop potential, these characteristics hardly vary over time, so that we allow for flexible, year-specific effects of the structural characteristics as measured in 2003. We first consider structural features with respect to education, as individuals with different levels of education may face different employment prospects over time. In row (7), we add employment shares by education (with a college degree, with completed vocational training both interacted with year dummies) to the standard set of covariates, and in row (8) we add the number of school and university students (as share of the working-age population and interacted with year dummies) as an additional regressor. Next, we investigate whether the results are driven by industry-specific shocks that may be, for some reason, correlated with PV installations. Row (9) allows for flexible, year specific shocks to the main sectors of the economy—agriculture, manufacturing, and construction (services serve as a baseline)—by including the employment share in each of these industries (interacted with year dummies) as control variables. Finally, row (10) allows for both industry and education specific shocks by adding the employment

[36] The correlation coefficient between the number of apartments per building and the number of individually owned buildings per capita is -0.92.

[37] We use ownership structure as an alternative instrument in row (17) of Table 10 in Appendix D.2. Table 13 shows that single ownership is a strong predictor for PV installations.

shares by both industry and education to the empirical model. Neither of these alternative specifications substantially reduces the difference between the employment effects of PV installations across slack or tight labor markets.

Model Specification The last set of robustness checks alters the specification of the empirical model. In the main analyses of the paper, the variable measuring investments is the sum of a county's installed output capacity of PV systems smaller than 500 kWp. In row (11), we estimate the employment effects of total investments, i.e., the sum of a county's installed capacity regardless of the size of the systems. This results in a few PV systems of large size, most likely greenfield systems, driving a significant amount of the variation in (uncleaned) PV investments. As a result, the OLS coefficients drop significantly, and are equal for slack and tight labor markets in the cross-sectional split. Note, however, that the IV estimates in Table 10 remain at their baseline level, presumably because the variation of PV installations explained by the instrument—the remuneration potential for rooftop systems—primarily predicts variation in rooftop installations.[38]

Finally, we check whether the composition of the sample has an effect on the results. In row (12), we exclude the 52 counties from the sample that include establishments of solar panel manufacturers.[39] The concern here is that we pollute the estimates of the employment effects of PV installations with employment effects of the solar panel manufacturers, for which the German Renewable Energy Act constituted a significant demand shock, but which also faced increasing competition from abroad. The results with the restricted sample are very close to the baseline results, however, so that the main findings are unlikely to be driven by employment in solar panel manufacturing. This also corroborates the findings regarding the employment effects by industry in Section 5. Finally, rows (13) and (14) ask whether our findings are driven by city counties (*Kreisfreie Städte*) or rural counties (*Landkreise*). Given that buildings in rural counties are much more suitable for rooftop PV systems due to the availability of larger rooftops that are not shaded by neighboring buildings, it comes with

[38]One explanation for this finding is that the planning and installation of large greenfield PV systems is undertaken by more specialized firms than the installation of mostly small rooftop systems, so that local variation in demand for greenfield installations does not translate into local employment gains, in contrast to the variation in demand for rooftop systems. While, to the best of our knowledge, there is no hard data on the relative number of firms installing rooftop and greenfield systems, one indication for firms installing greenfield systems being more specialized is that the newest amendment of the Renewable Energy Act prescribes a procurement process for systems larger than 750 kWp. A cursory search for firms installing rooftop and greenfield systems, respectively, also suggests that the latter serve geographically much larger markets.

[39]The web portal "solarserver.de" lists the major German solar panel manufacturers and their locations: https://www.solarserver.de/service-tools/statistik-und-marktforschung/photovoltaik/unternehmen.html [last accessed on May 3rd, 2018]. About half of the establishments of solar manufacturers are located in former East Germany.

little surprise that our effects are mostly driven by rural counties.

C.2 IV Results

Table 10 performs the same robustness checks using IV as the ones performed via OLS in Table 9. In addition, Table 10 also shows that the IV results are robust to alternative definitions of the instrument. Apart from the already well-known differences in the magnitudes of the coefficients, the robustness checks as estimated via IV lead, by and large, to the same conclusions as the ones estimated via OLS. For this reason, we abstain from describing each of the rows in Table 10, but focus instead on those rows in which the OLS and the IV results differ.

Determinants of Rooftop Potential The first set of robustness checks adds those variables as covariates that are predictors for the estimate of rooftop potential.[40] Given equation (2), the functional form of the instrument *remuneration potential*, these are particularly demanding for the IV strategy. This is due to the fact that controlling more strongly for the cross-sectional determinants of rooftop potential results in identification relying more strongly on the interaction of rooftop potential and radiation. Nevertheless, the main findings are robust to adding these determinants. The most noticeable difference to the OLS results is that adding the interaction of a county's area with year dummies in row (1) leads to larger coefficient estimates in almost all subsamples. These estimates are, however much less precise than the baseline results. Similar to the OLS estimates, adding the number of apartments per building reduces the estimates, presumably (and as discussed in Appendix C.1) due to their strong predictive power for PV installations.

Structural Characteristics The second set of robustness checks adds structural characteristics as additional covariates. As for OLS, these additional controls do not alter the results substantially. In comparison to the OLS results, the IV coefficients and standard errors are inflated in the cross-sectional split when we control for industry structure. Most likely, this is a result of the instrument becoming weaker due to the addition of a large number of regressors that vary in the cross-section.

Model Specification The third set of robustness checks modifies the model specification. The biggest difference of the IV estimates to the OLS estimates of Table 9 in rows (11) to (14) is that the coefficients of the IV results do not drop significantly when we consider all the PV installations in the data (instead of only the smaller systems with a capacity of less than

[40] Appendix A.2 provides the details of this estimation.

Table 10: Robustness: IV

	Time series split					Cross-sectional split				
	Slack		Tight		P-Val	Slack		Tight		P-Val
	Coeff	SE	Coeff	SE		Coeff	SE	Coeff	SE	
(0) Baseline	148.43	45.38	22.60	10.86	0.003	180.11	37.73	30.53	12.01	0.000
Determinants of Rooftop Potential										
(1) Area × year	317.95	111.89	0.00	14.99	0.002	369.11	116.01	64.54	20.12	0.005
(2) Total settlement area × year	152.88	47.24	21.71	10.74	0.002	216.09	41.65	31.29	11.95	0.000
(3) Total dwelling area × year	147.62	45.20	23.83	10.44	0.002	200.52	40.01	28.87	12.30	0.000
(4) Population density × year	138.95	49.92	14.25	10.94	0.006	178.22	42.07	25.07	13.56	0.000
(5) Square meters p.c. × year	120.86	49.37	6.71	13.22	0.010	200.36	62.49	29.54	14.38	0.003
(6) Apartments/building × year	75.29	50.85	9.50	11.82	0.107	144.03	49.46	16.12	13.88	0.005
Structural Characteristics										
(7) Education share × year	169.61	58.98	29.44	14.46	0.008	240.28	49.87	50.85	16.97	0.000
(8) School & uni students × year	141.48	48.35	25.80	12.52	0.007	200.17	46.28	31.57	15.83	0.000
(9) Industry share × year	172.92	58.21	19.76	16.23	0.004	360.86	208.59	56.36	22.31	0.075
(10) Industry & education share × year	184.38	62.45	24.18	17.11	0.005	395.08	218.71	61.10	22.74	0.066
Model Specification										
(11) Investments uncleaned	111.23	39.84	19.73	9.86	0.010	293.11	163.36	21.08	8.27	0.048
(12) Without solar panel manufacturers	165.87	54.19	23.02	10.93	0.004	196.74	36.69	37.04	12.98	0.000
(13) Only city counties	31.14	434.81	99.41	167.96	0.564	266.39	172.82	265.03	158.37	0.498
(14) Only rural counties	141.37	43.21	20.58	10.35	0.002	97.04	23.95	26.77	13.05	0.003
(15) Instr.: costs & income	179.81	55.67	21.48	12.05	0.002	168.24	45.95	30.44	13.98	0.002
(16) Instr.: rooftop-p × radiation × year	58.65	24.13	21.43	6.18	0.054	119.72	29.72	25.58	9.72	0.001
(17) Instr.: ownership × radiation × year	80.77	31.09	32.87	8.15	0.055	158.23	46.89	22.77	11.88	0.002

Notes. This table presents the results of various modifications of the baseline specification of Table 2. It provides IV estimates of the employment effect of PV installations conditional on the state of the labor market according to both the time series and the cross-sectional split of the sample. Each row of the table represents the result of a different modification of the baseline specification; see the text for details. Columns entitled "Coeff" report the IV coefficient estimate of *installed capacity p.c.* for the subsample with slack and tight labor market, respectively. Columns entitled "SE" report the corresponding standard errors, clustered at the level of 94 spatial planning regions. Columns entitled "P-Val" report the p-value for the test of the null hypothesis that the employment effect of PV installations is smaller in a slack labor market than in a tight labor market.

500 kWp) as our measure of physical investments in row (11). The drop in the OLS results is most likely due to the small local employment effects of large commercial greenfield systems that are installed by specialized firms. In contrast, the instrument captures the potential profitability of *rooftop* systems so that instrumented investments are much less prone to "measurement error" due to considering all investments in solar energy.

Alternative Instrument Definitions Finally, in rows (15) to (17) we explore whether alternative definitions of the instrument alter the results. The first stages of all alternative instruments are reported below.

Row (15) splits up the time-varying instrument *remuneration potential* as defined by equation (2) into the present value of the net income stream (the product of *rooftop potential* and the discounted sum of the net income flows in the second line of (2)) and the current installation costs (the product of *rooftop potential* and *costs*), so that there are two time-varying instruments. The remaining two instruments rely on cross-sectional variation only and are interacted with year dummies to obtain (a large number of) time-varying instruments. Row (16) employs *rooftop potential* × *radiation* as the instrument, with a similar motivation as before: rooftop potential and radiation jointly determine the return on investment. Row (17), in turn, exploits the alternative idea that the ownership structure of buildings affects the transaction costs of installing a rooftop PV system. As mentioned already in Appendix C.1, there has to be unanimous consent of all owners of a building for alterations to the building as a whole, including the installation of solar panels. The implied transaction costs are absent for buildings owned by single individuals or firms. The number of buildings with a single owner (relative to the working-age population) is hence a valid instrument if the ownership structure is independent of labor market developments, arguably a stronger assumption than for the stock of available rooftop space. One potential concern for this idea is that in growing economies (and tight housing markets), individuals may be more inclined to join ownership cooperations, invalidating this potential instrument.

The results for all three of these alternative IV strategies show that the estimated magnitudes of the employment gains in slack and tight labor markets do not differ from the baseline estimates in the cross-sectional split. The same is true for the time series split in the specification with costs and income as the instruments (row (15)). Instrumenting via year-specific effects of *rooftop potential* × *radiation* and *single ownership* × *radiation* leads to smaller estimated employment gains in the time-series split (rows (16) and (17)). However, the estimates also become more precise, so that we can reject the null hypothesis that the employment gains are smaller in slack than in tight labor markets at the ten percent level (with p-values at or below 0.055).

Table 11: First Stage: Costs and Income

Split along	Installed Capacity p.c. (in MWp)				
		Time series		Cross-section	
	Baseline (1)	Slack (2)	Tight (3)	Slack (4)	Tight (5)
Income p.c. (Mio Euro)	0.0123***	0.0047***	0.0247***	0.0037**	0.0179***
	(0.0018)	(0.0009)	(0.0035)	(0.0015)	(0.0026)
Cost p.c. (Mio Euro)	−0.0204***	−0.0093***	−0.0289***	−0.0080***	−0.0281***
	(0.0023)	(0.0021)	(0.0038)	(0.0016)	(0.0034)
Population growth	0.0003***	0.0001	0.0000	0.0001	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Construction p.c.	0.0029**	0.0009	0.0025	−0.0014	0.0049***
	(0.0013)	(0.0006)	(0.0023)	(0.0013)	(0.0018)
County fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
F-statistic instrument	58.64	16.25	29.15	17.99	54.08
Observations	4000	2044	1956	1798	2202

Note: The dependent variable *installed capacity p.c.* are photovoltaic installations measured in megawatt peak (MWp) normalized by the working-age population in 2003 (as indicated by "p.c." for "per capita"). *Income p.c.* is the net present value of the potential income stream for PV systems of the size of the county's rooftop potential, given the local solar radiation and the applicable feed-in tariff. *Cost p.c.* is the time-varying installation cost of PV systems of the size of the county's rooftop potential. *Population Growth* is the ratio of the working-age population in a given year to the working-age population in 2003. *Construction p.c.* is the number of residential and non-residential buildings completed in a given year. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). *F-statistic instrument* is the Kleibergen-Paap F-statistic of the instruments (*income p.c.* and *cost p.c.*). Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Tables 11, 12, and 13 report the associated first stages for the alternative instruments used in rows (15), (16), and (17), respectively. In Table 11, the present value of the net income stream predicts investment positively and costs predict investment negatively, as one would expect. The first stage F-statistics range from 16.25 to 58.64, indicating strong predictive power. Due to the interaction of *rooftop potential* × *radiation* with year dummies, we have nine instruments in Table 12. All interactions predict investment positively with F-statistics of over 14.74 in all specifications. There are missing coefficients in the time series split, as in some years not a single county is classified as having either a slack or tight labor market. Last, Table 13 shows that *single ownership* × *radiation* (× *year*) also positively predicts investment. However, in our cross-sectional splits the predictive power is somewhat lower with a F-statistic of around seven.

Table 12: First Stage: Rooftop Potential × Radiation × Year

	Installed Capacity p.c. (in MWp)				
Split along		Time series		Cross-section	
	Baseline	Slack	Tight	Slack	Tight
	(1)	(2)	(3)	(4)	(5)
Rooftop potential p.c. × *radiation*					
× 2004	0.0051***	0.0051***	0.0187***	0.0042***	0.0063***
	(0.0009)	(0.0011)	(0.0034)	(0.0009)	(0.0016)
× 2005	0.0069***	0.0068***	0.0090**	0.0057***	0.0074***
	(0.0008)	(0.0010)	(0.0039)	(0.0010)	(0.0014)
× 2006	0.0047***	0.0045***	.	0.0040***	0.0050***
	(0.0006)	(0.0007)	.	(0.0011)	(0.0013)
× 2007	0.0073***	0.0071***	.	0.0043***	0.0090***
	(0.0013)	(0.0014)	.	(0.0013)	(0.0026)
× 2008	0.0135***	0.0075***	0.0029	0.0060***	0.0183***
	(0.0025)	(0.0013)	(0.0040)	(0.0019)	(0.0044)
× 2009	0.0314***	.	0.0212***	0.0130***	0.0419***
	(0.0041)	.	(0.0041)	(0.0024)	(0.0063)
× 2010	0.0490***	0.0558***	0.0389***	0.0239***	0.0607***
	(0.0050)	(0.0070)	(0.0050)	(0.0041)	(0.0067)
× 2011	0.0385***	0.0320***	0.0284***	0.0211***	0.0469***
	(0.0034)	(0.0034)	(0.0042)	(0.0024)	(0.0042)
× 2012	0.0218***	.	0.0121***	0.0115***	0.0276***
	(0.0021)	.	(0.0040)	(0.0021)	(0.0032)
Population growth	0.0002***	0.0001	0.0001	0.0001	0.0004***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Construction p.c.	0.0026**	0.0008	0.0006	−0.0012	0.0048***
	(0.0012)	(0.0005)	(0.0019)	(0.0012)	(0.0017)
County fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
F-statistic instrument	28.22	26.14	28.04	14.74	34.48
Observations	4000	2044	1956	1798	2202

Note: The dependent variable *installed capacity p.c.* are photovoltaic installations measured in megawatt peak (MWp) normalized by the working-age population in 2003 (as indicated by "p.c." for "per capita"). *Rooftop potential p.c.* × *radiation* is the interaction of *rooftop potential p.c.,* the roof space suitable for photovoltaic installations (as estimated in Appendix A.2 and measured in kWp) and the county's average yearly radiation (measured in kWh). *Rooftop potential p.c.* × *radiation* interacted with year dummies constitutes the set of time-varying instruments. There are missing coefficients in the time series split, as in some years not a single county is classified as having either a slack or a tight labor market. *Population Growth* is the ratio of the working-age population in a given year to the working-age population in 2003. *Construction p.c.* is the number of residential and non-residential buildings completed in a given year. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). *F-statistic instrument* is the Kleibergen-Paap F-statistic of the instruments. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: First Stage: Single Ownership × Radiation × Year

	Installed Capacity p.c. (in MWp)				
Split along		Time series		Cross-section	
	Baseline	Slack	Tight	Slack	Tight
	(1)	(2)	(3)	(4)	(5)
Single ownership p.c. × radiation					
× 2004	0.0781***	0.0809***	0.2390***	0.0432***	0.1280***
	(0.0182)	(0.0250)	(0.0524)	(0.0158)	(0.0391)
× 2005	0.1122***	0.1160***	0.2245***	0.0763***	0.1511***
	(0.0176)	(0.0217)	(0.0457)	(0.0158)	(0.0389)
× 2006	0.0787***	0.0823***	.	0.0626***	0.0740**
	(0.0136)	(0.0172)	.	(0.0168)	(0.0360)
× 2007	0.1349***	0.1383***	.	0.0775***	0.1678**
	(0.0272)	(0.0317)	.	(0.0164)	(0.0656)
× 2008	0.2555***	0.1330***	−0.0129	0.1237***	0.3678***
	(0.0515)	(0.0250)	(0.0594)	(0.0246)	(0.1169)
× 2009	0.5344***	.	0.3297***	0.2450***	0.8157***
	(0.0942)	.	(0.0541)	(0.0451)	(0.1876)
× 2010	0.8016***	1.0217***	0.6010***	0.3939***	1.1540***
	(0.1166)	(0.2240)	(0.0746)	(0.0648)	(0.2223)
× 2011	0.6275***	0.6045***	0.4233***	0.3359***	0.9172***
	(0.0904)	(0.0901)	(0.0578)	(0.0604)	(0.1544)
× 2012	0.3564***	.	0.1631***	0.1877***	0.5172***
	(0.0539)	.	(0.0557)	(0.0332)	(0.1122)
Population growth	0.0002**	0.0001	0.0001	0.0001	0.0005***
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0002)
Construction p.c.	0.0025*	0.0007	0.0011	−0.0007	0.0046**
	(0.0015)	(0.0005)	(0.0023)	(0.0013)	(0.0020)
County fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
F-statistic instrument	10.30	13.56	16.93	7.58	6.80
Observations	4000	2044	1956	1798	2202

Note: The dependent variable *installed capacity p.c.* are photovoltaic installations measured in megawatt peak (MWp) normalized by the working-age population in 2003 (as indicated by "p.c." for "per capita"). *Single ownership p.c.* × *radiation* is the number of individually owned residential buildings per capita times the county's average yearly radiation (measured in kWh). *Single ownership p.c.* × *radiation* interacted with year dummies constitutes the set of time-varying instruments. There are missing coefficients in the time series split, as in some years not a single county is classified as having either a slack or a tight labor market. *Population Growth* is the ratio of the working-age population in a given year to the working-age population in 2003. *Construction p.c.* is the number of residential and non-residential buildings completed in a given year. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). *F-statistic instrument* is the Kleibergen-Paap F-statistic of the instruments. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Appendix to Section 5: Discussion of the Mechanism

This section performs the analyses outlined in Section 5 for the full sample, i.e. without the sample splits (Appendix D.1), and using IV instead of OLS (Appendix D.2).

D.1 Employment Gains by Sector and Geographic Spillovers: Full Sample

Table 14 reports the results for employment gains by industry.[41] As should be expected, the employment gains due to PV installations primarily originate from the high-exposure sectors, while local services contribute around 40% to the overall employment increase. For the "other" sector the coefficient is economically close to zero, and we cannot statistically reject the hypothesis that it actually equals zero. The concentration of the effect in the high-exposure sector suggests that we indeed measure the effect of PV investments on employment.

Table 15 reports the employment gains due to PV installations for the full sample when we account for spatial spillovers.[42] The results show that the spatial spillovers of PV installations are small at best, both when estimated via OLS (Panel A) or IV (Panel B). Compared to the baseline estimates in column (1), the employment effect of within-county PV installations remains unchanged when adding PV installations in neighboring counties as an additional independent variable. Moreover, the estimates of the effect of the neighboring counties' PV installations on employment are at least one order of magnitude smaller than the effect of the within-county PV installations. This holds for all definitions of the set of neighboring counties and for both the OLS and IV estimates. Taken together, the results in Table 15 suggest that the labor market for PV installations is very local in nature, so that the baseline estimates are a good approximation of the total employment gains due to differential investments across regions.

D.2 Employment Gains by Sector and Geographic Spillovers: IV Results

For brevity, Section 5 discusses the additional results regarding the employment gains across sectors and geographic spillovers in terms of their OLS estimates. This appendix reports the IV results of the exact same analyses. The general observation is that the IV results qualitatively mirror the OLS results. The main difference is in the magnitude of the estimates obtained via both strategies, as should be expected given the magnitude differences in the main OLS and IV results in Tables 1 and 2, respectively.

[41] See Section 5 for the classification of industries as "high-exposure," "local," and "other."

[42] See Section 5 for the definition of neighboring counties.

Table 14: Sectoral Employment: Baseline

	Industry-specific Employment p.c.					
	OLS			IV		
	High-exposure (1)	Local (2)	Other (3)	High-exposure (4)	Local (5)	Other (6)
Capacity p.c. (MWp)	15.04***	8.37***	−4.63	23.65***	16.98***	−3.47
	(4.74)	(2.36)	(8.58)	(5.92)	(3.62)	(11.48)
Population growth	0.02*	0.04***	0.30***	0.02	0.04***	0.30***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Construction p.c.	−0.09	−0.17**	0.11	−0.09	−0.16**	0.11
	(0.12)	(0.08)	(0.24)	(0.12)	(0.08)	(0.24)
County fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Jobs per €100,000	0.48	0.27	−0.15	0.76	0.54	−0.11
F-statistic instrument				88.21	88.21	88.21
Observations	4000	4000	4000	4000	4000	4000

Note: The dependent variable in columns (1) and (4) is employment in the high-exposure sectors (construction and related industries) normalized by the working-age population in 2003 (indicated by "p.c." for "per capita"). The dependent variable in columns (2) and (5) is employment p.c. in local, non-tradable industries (wholesale, retail, hospitality, local services). The dependent variable in columns (3) and (6) is employment p.c. in all remaining industries. Employment by industry is measured annually on June 30th. Table 6 in Appendix A.1 provides details of the industry classifications. All other variables are defined as in Tables 1 and 2. In columns (4) to (6), installed *capacity p.c.* is instrumented by *remuneration potential p.c.* as defined in Section 3.1. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Employment Gains by Sector Table 16 reports the IV estimates of the employment gains due to PV installations in slack and tight labor markets in each of the subsectors defined by the partition of employees into high-exposure, local, and all other sectors. As for the OLS results in Table 4, Panel A presents the results for the time series split, and Panel B presents the results for the cross-sectional split. As before, two results stand out. First, in both slack and tight labor markets, PV installations led to a statistically significant increase in employment only in the high-exposure and local non-tradable sectors. Second, the difference of the employment gains in slack and tight labor markets is driven by high-exposure and local industries. In both the time series and the cross-sectional split, the difference in employment gains between slack and tight labor markets is sizable. Also, for the IV results we reject the null hypothesis that the employment gains are smaller in slack than in tight labor markets for the high-exposure and local sector in both sample splits. This is a stronger result than the one obtained from OLS, where we reject this hypothesis only for half of the respective coefficients. In sum, the IV results are hence similar if not stronger than the findings from OLS reported in Section 5.

Geographic Spillovers Next, we use the IV strategy to test for geographic spillovers along the line of the corresponding OLS analysis in Section 5. As for OLS, we consider three definitions of neighboring counties: all other counties within the same spatial planning region (*Raumordnungsregion*), the five closest counties based on the distance between both counties' most populous municipalities, and the ten closest counties. For the IV specification, we instrument for the neighbors' investments via the sum of the estimated remuneration potential in the neighboring counties, normalized by the working-age population of the county of interest. Given this, we estimate an extended version of the main empirical model (1) that includes aggregate PV installations in the neighboring counties as additional covariate and that instruments the county's own as well as the neighboring PV installations via the county's own and the neighbors' aggregate remuneration potential. We classify counties as having slack or tight labor markets according to their own unemployment rate as described in Section 3.2, exactly as in the main empirical analyses.

Table 17 reports the IV estimates. Panel A contains the results of the time series split and Panel B contains the results of the cross-sectional split. In both splits and in all three definitions of a county's set of neighbors, the effect of additional PV installations in geographically proximate regions is at least one order of magnitude smaller than the effect of additional installations within the county. In addition to their small magnitude, these coefficients are mostly statistically insignificant. The estimated effects of the demand spillovers also do not differ between slack and tight labor markets, while the differences of the employment gains due to the within-county investments remain at the same level as in Table 2, the main IV specification. As for the OLS results in Table (5), we hence conclude that the employment effects of PV installations are very local in nature, so that demand spillovers are unimportant for the interpretation of our main findings.

Table 15: Spillovers from Neighboring Counties: Baseline

	Employment Rate			
	Base-line (1)	Planning Region (2)	5 Closest Counties (3)	10 Closest Counties (4)
	Panel A: OLS			
Capacity p.c. (MWp)	19.98***	19.38***	20.20***	18.96***
	(6.35)	(5.99)	(5.63)	(5.87)
Neighboring capacity p.c.		0.32	−0.08	0.20
		(1.21)	(0.85)	(0.49)
Jobs per €100,000	0.64	0.62	0.65	0.61
	Panel B: IV			
Capacity p.c. (MWp)	52.57***	50.20***	52.78***	50.98***
	(13.60)	(13.76)	(13.63)	(13.25)
Neighboring capacity p.c.		1.17	−0.06	0.28
		(2.01)	(1.49)	(0.73)
Jobs per €100,000	1.68	1.61	1.69	1.63
F-statistic instrument(s)	88.21	45.15	53.91	47.71
PopGrowth & construction	yes	yes	yes	yes
County fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	4000	4000	4000	4000

Note: *Neighboring capacity p.c.* is the sum of PV installations (measured in MWp and normalized by the working-age population) across all other counties in the same spatial planning region (column (2)), the 5 closest counties (column (3)), or the 10 closest counties (column (4)). Closeness is measured by the distance between the counties' most populous municipalities. In Panel B, *capacity p.c.* and *neighboring capacity p.c.* are instrumented by *remuneration potential p.c.* as defined in Section 3.1 and the sum of *remuneration potential* in the set of neighboring counties, normalized by the (main) county's working-age population. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). All other variables are defined as in Tables 1 and 2. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Sectoral Employment Conditional on Slack: IV Results

	Industry-specific Employment p.c.					
	High-exposure		Local		Other	
	Slack (1)	Tight (2)	Slack (3)	Tight (4)	Slack (5)	Tight (6)
	Panel A: Time Series Split					
Capacity p.c. (MWp)	36.99**	6.91*	42.81***	10.45***	18.55	4.23
	(15.95)	(3.57)	(12.99)	(3.29)	(34.57)	(9.28)
P-val slack < tight	0.033		0.006		0.342	
Jobs per €100,000	1.18	0.22	1.37	0.33	0.59	0.14
F-statistic instrument	22.11	59.15	22.11	59.15	22.11	59.15
Observations	2044	1956	2044	1956	2044	1956
	Panel B: Cross-Sectional Split					
Capacity p.c. (MWp)	52.13**	12.56**	44.63***	11.90***	42.88	−3.86
	(24.26)	(5.71)	(16.60)	(3.39)	(32.22)	(11.85)
P-val slack < tight	0.057		0.026		0.081	
Jobs per €100,000	1.67	0.40	1.43	0.38	1.37	−0.12
F-statistic instrument	28.43	79.66	28.43	79.66	28.43	79.66
Observations	1783	2189	1783	2189	1783	2189
PopGrowth & construction	yes	yes	yes	yes	yes	yes
County fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Note: The dependent variable in columns (1) and (2) is employment in the high-exposure sectors (construction and related industries) normalized by the working-age population in 2003 (indicated by "p.c." for "per capita"). The dependent variable in columns (3) and (4) is employment p.c. in local, non-tradable industries (wholesale, retail, hospitality, local services). The dependent variable in columns (5) and (6) is employment p.c. in all remaining industries. Employment by industry is measured annually on June 30th. Table 6 in Appendix A.1 provides details of the industry classifications. *Capacity p.c.* are yearly photovoltaic installations measured in megawatt peak (MWp), which are instrumented by *remuneration potential p.c.* as defined in Section 3.1. Except for the dependent variables, the empirical specifications are identical to the one in Table 2. In particular, the *year fixed effects* are estimated at the level of the state × county type (rural or urban county). Panel A reports the results for the time series split and Panel B reports the results for the cross-sectional split. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Spillovers from Neighboring Counties: IV Results

	Employment Rate					
	Planning Region		5 Closest Counties		10 Closest Counties	
	Slack (1)	Tight (2)	Slack (3)	Tight (4)	Slack (5)	Tight (6)
	Panel A: Time Series Split					
Capacity p.c. (MWp)	144.40***	18.35	147.19***	18.90	144.50***	14.84
	(48.55)	(11.57)	(46.72)	(12.03)	(47.33)	(11.86)
Neighboring capacity p.c.	1.92	1.87	0.33	1.04	0.68	1.24
	(5.61)	(1.39)	(4.58)	(1.43)	(2.29)	(0.83)
P-val slack < tight	0.005		0.004		0.003	
Jobs per €100,000	4.63	0.59	4.72	0.61	4.63	0.48
F-statistic instruments	10.95	28.74	15.96	32.42	10.96	31.66
Observations	2044	1956	2044	1956	2044	1956
	Panel B: Cross-Sectional Split					
Capacity p.c. (MWp)	193.21***	33.49**	200.80***	40.22***	201.16***	39.14***
	(41.08)	(13.01)	(39.31)	(13.85)	(39.51)	(13.12)
Neighboring capacity p.c.	−2.37	−2.21	−3.16*	−3.62	−1.67	−1.94*
	(2.36)	(2.72)	(1.78)	(2.31)	(1.03)	(1.11)
P-val slack < tight	0.000		0.000		0.000	
Jobs per €100,000	6.19	1.07	6.43	1.29	6.44	1.25
F-statistic instruments	11.72	40.21	10.43	40.68	10.60	39.02
Observations	1783	2189	1783	2189	1783	2189
PopGrowth & construction	yes	yes	yes	yes	yes	yes
County fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Note: *Neighboring capacity p.c.* is the sum of PV installations (measured in MWp and normalized by the working-age population) across all other counties in the same spatial planning region (columns (1) and (2)), the 5 closest counties (columns (3) and (4)), or the 10 closest counties (columns (5) and (6)). Closeness is measured by the distance between the counties' most populous municipalities. Installed *capacity p.c.* and *neighboring capacity p.c.* are instrumented by *remuneration potential p.c.* as defined in Section 3.1 and the sum of *remuneration potential* in the set of neighboring counties, normalized by the (main) county's working-age population. *F-statistic instruments* reports the Kleibergen-Paap F-statistic of both excluded instruments. The *year fixed effects* are estimated at the level of the state × county type (rural or urban county). All other variables are defined as in Table 2. Panel A reports the results for the time series split and Panel B reports the results for the cross-sectional split. Standard errors (in parentheses) are clustered at the level of 94 spatial planning regions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.